ESSAYS ON HUMAN CAPITAL, ENVIRONMENT, AND DEVELOPMENT

A Dissertation

Presented to the Faculty of the Graduate School

of Cornell University

in Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

by

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May 2019

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Cornell University 2019

This dissertation examines how government policies and natural environment, independently and interactively, influence education outcomes as well as if and how households or individuals adapt to fixed or changing features of the natural environment.

Biographical Sketch

Maulik is a native of Bombay, India. He received undergraduate education from University of Mumbai ('09), and attended Masters program in Economics at Tufts University ('12). Prior to beginning his PhD at Cornell, he worked as a Research Associate at IFMR Centre for Micro Finance/ MIT Poverty Action Lab (J-PAL) in India.

This dissertation is dedicated to the memory of my grandparents, Gaurishankar Jagnani, Ramdulari Jagnani, and Achukidevi Agarwal, who passed away while I was pursuing my PhD.

Acknowledgements

I am very grateful to my advisors, Chris Barrett, Jim Berry, Doug Miller, and Eswar Prasad, for their guidance over the course of this dissertation. I would like to thank my father, Vimal Kumar Jagnani, mother, Madhu Jagnani, and brother, Samarth Jagnani, for their unrelenting support.

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Chapter 1

Introduction

The foremost policy challenges confronting our planet include (i) improving educational outcomes for the 40% of the world's population that are under the age of 25 (402) and (ii) adapting to the impacts of climate change that threaten to decrease global incomes by over 20% by 2100 (73). Both these issues are most pressing in the developing world: almost 90% of the global population between ages 10 and 24 live in low- and lower middle-income countries, where only 1 in 3 children complete secondary school and fewer than 1 in 5 primary school children are proficient in math and reading (402); and, developing countries will experience disproportionately higher temperatures as well as the strongest increase in variability (43; 190) , where predominantly agrarian livelihoods are hypothesized to be especially fragile in the face of weather shocks (111; 113; 315; 352; 406).

In "Essays on Human Capital, Environment, and Development", I study how government policies and natural environment, independently and interactively, influence education outcomes as well as if and how households or individuals adapt to fixed or changing features of the natural environment.

Education offers a wide range of benefits that extend beyond increases in labor market productivity. Improvements in education can lower crime, improve health, and increase voting and democratic participation (250). A complex debate surrounds the magnitude of public investments directed towards different levels of education. Investments in primary education are less politically contentious, as primary education is perceived to be a broad public good with few distributional issues, while public investments in higher education are often decried as an income transfer to elite socioeconomic subpopulations, magnifying income inequality (348). Such analyses ignore any potential developmental 'spillovers' of higher education investments. If public investments in higher education increase lower levels of schooling, strengthening the entire education system, policymakers should account for these benefits and reevaluate the social returns to investments in higher education. In the first substantive chapter of this dissertation (Jagnani and Khanna 2019), I present the first estimates of the effects of higher education investments on lower levels of schooling. Using the roll-out of elite public colleges in India, we show that investments in higher education increased educational attainment among school-age children. Private schools entered districts with new elite public colleges, and students switched from public to private schools. In addition, elite public colleges crowded in investments in electricity, roads, and water services. We find suggestive evidence that public investments in infrastructure may have reduced setup costs for private schools, and consequently, travel costs for school-going children. Our back-of-the-envelope calculations indicate that the indirect benefits of elite public colleges due to transfers to private schools and returns to extra years of primary and secondary schooling, are at least half the size of the direct benefits accrued through the training of undergraduate and graduate students.

Existing evidence, almost exclusively from affluent countries, suggests that investment in higher education generates long-term local effects through direct increases in the supply of human capital and greater innovation (225; 405). However, such mechanisms may be less relevant for lower-income countries. Higher education institutions in India are quite small in relation to the size of the local population, as average enrollment is just over 700 students (178), so benefits to the local economy from increases in human capital endowment might not be substantial. In addition, research is not the primary mandate of higher education institutions in India, and they lag significantly behind universities in high- and middle-income countries in terms of research output. We show that higher education institutions facilitate educational attainment among school-age children in India, indirectly increasing the supply of human capital. In India, over 80 million children are out of school (90). Thus, optimally targeted higher education investments may strengthen both the foundations of the education system (i.e., primary and secondary school), as well as tertiary education, since lower levels of schooling are critical as prerequisites for higher education.

In policy discussions aimed at improving educational outcomes, another neglected influence is the time of day at which the sun sets, something that is determined by discretionary time zone policies and can vary considerably both across and within countries. Each evening the sun sets more than 90 minutes later in west India than in the east. This is because the whole country follows Indian Standard Time. Similarly, in China, all clocks are set to Beijing Time, which means that the sun sets three hours later in the west than in the east. The sun sets at least an hour later in Madrid than in Munich because Franco's Spain switched clocks ahead one hour to be in sync with Nazi Germany in 1940, even though Spain is geographically in line with Britain, which is in the time zone one hour behind Germany. Similarly, for various historical reasons, clocks in many places including Algeria, Argentina, France, Russia, Senegal, and South Sudan are set ahead of their (solar) time and see the sun set later in the day.

My second chapter (Jagnani 2019) provides the first evidence that by generating large discrepancies in when the sun sets across locations, these arbitrary clock conventions help to determine the geographical distribution of educational attainment levels. Using data from India, China, and Indonesia, I show school-age children in locations that experience later sunsets attain fewer years of education due to the negative relationship between sunset time and sleep, and the consequent productivity effects of sleep deprivation. When the sun sets later, children go to bed later; by contrast, wake-up times are not regulated by solar cues. Sleep-deprived children have lower productive effort; later sunset reduces students' time spent on homework or studying, while increasing time spent on indoor leisure for all children. Later sunsets are also associated with fewer hours of sleep and lower wages among adults.

The timing of natural light is determined by time zones and is therefore predictable across locations and seasons. If sleep is important for productivity, it is surprising households that fail to adjust their sleep schedules in response to later sunset. I show that the non-poor adjust their sleep schedules when the sun sets later. Sunset-induced sleep deficits are most pronounced among the poor, especially at times when households face severe financial constraints, consistent with recent evidence that psychological consequences associated with poverty affect decision-making (259; 354). Because education is both a driver of economic growth and a means to reduce income inequality (41), these results imply that sunset time associated with geographical location may contribute to persistent poverty and worsening inequality. Back of the envelope estimates suggest that India would accrue annual human capital gains of over US$4.2 billion (0.2% of GDP) if it switches from the existing time zone policy to a two-time zone policy: UTC+5 for western India and UTC+6 for eastern India. But there may be benefits associated with the synchronization of daily schedules across the country, and one must be cautious about proposing changes to the existing time zone policy without a thorough cost-benefit analysis. Therefore, I also explore two other policy interventions that may mitigate the effects of later sunset on children's educational outcomes. One is later school start times; the other is social protection programs. I find suggestive evidence that later school start times allow children to compensate for later bedtimes by waking up later and attenuate the effect of later sunset on schooling outcomes. Meanwhile, each additional year of exposure to India's conditional cash transfer program, The Mahtama Gandhi National Rural Employment Guarantee Act (MNREGA), mitigates the effect of later sunset on children's educational outcomes.

I provide evidence that arbitrary government policies may interact with fixed features of the natural environment to produce bad economic outcomes. This paper contributes to a new literature that examine how discretionary clock settings – by generating differences in the timing of natural light – affect economic outcomes (136; 363). Two studies examine the relationship between daylight savings time (DST) transitions and test scores but find contrasting results (166; 197). In any case, if one were to compare short-run effects of sleep deprivation from daylight savings time onset, to the long-run effects of sleep deprivation at issue in my paper, two differences have offsetting effects. First, the effects of sleep deprivation on education production might accumulate. The DST transition may only affect sleep for a few days, while later sunset affects sleep every day. Second, there may be adaptation to a permanent shift in sunset time. In addition, within this literature, a small set of papers evaluate the implications of the relationship between sunset time and sleep. (173) observe associated impacts of later sunset on adult wages in the US, while (175) and (174) investigate consequent effects on adult health outcomes in the US and China, respectively. I provide the first evidence that arbitrary clock conventions – by generating long-term differences in sleep – help determine the geographic distribution of educational attainment levels. Because education is associated with increases in labor productivity and improvement in health outcomes (107; 140), policies that promote children's sleep may also improve later-life well-being in locations exposed to later sunsets. Lastly, several recent studies that examine the short-term consequences of later school start times on students' academic performance in the US (86; 195). These effects (or lack thereof) are mediated through changes in children's time use, although these papers do not observe children's sleep or consequent trade-offs with other uses of time. My results provide the first evidence on the long-run importance of child sleep for learning outcomes.

The changing features of the natural environment may independently affect educational outcomes. The fact that the earth's climate is warming has renewed interest in the effects of weather on economic outcomes (119; 268). However, a critical yet understudied question is the impact of temperature on human capital production, particularly in developing countries, where predominantly agrarian livelihoods are climate-exposed, and where individuals are unable to consumption smooth over aggregate weather shocks (124; 334).

In my third chapter (Garg, Jagnani, and Taraz 2019), using multiple data sets from India, I show that higher temperatures reduce math and reading test score among school-age children. Agricultural income is one mechanism driving this relationship. Hot days during the growing season reduce agricultural yields and test scores with comparatively modest effects of hot days in the non-growing season. Importantly, the roll-out of a workfare program, by providing a safety net for the poor, substantially weakens the link between temperature and test scores. Back of the envelope estimates indicate that by the end of the century, over all 12 years of a child's schooling, higher temperatures would reduce the effective years of schooling the child has received by 2 years. Our results imply that absent social protection programs, higher temperatures will have large negative impacts on human capital production of poor populations in agrarian economies.

Within the literature that examines the relationship between weather and economic outcomes, a small number of new papers have considered the relationship between temperature and human capital (98; 179; 306). These studies have been set in developed countries, limiting them to a singular channel: the physiological effect of day-of-test temperature on math, but not reading performance. However, they fail to find evidence for the effects of temperature on test scores over a time horizon longer than the day of the test. (98) does find that longer-run exposure to heat stress during the summer months affects both math and reading scores in South Korea, but the study is ambivalent about the underlying mechanism. In this paper, we provide the first evidence for the day-of-test physiological effects of heat stress, and more importantly, the effects of longer-run temperature on human capital, in a developing country context. Furthermore, in contrast to previous work, we find evidence that one mechanism underlying the effects of longer-run temperature on test scores is agricultural income. Our work highlights the fact that a shared environmental issue – high temperatures – may have vastly different mechanisms and impacts depending on the country context, emphasizing the importance of examining environmental issues in developing countries (181). In addition, there exists a growing literature on the role of public programs in helping households and individuals cope with environmental shocks (6; 126; 183). Our paper is the first to provide evidence on the role of public programs in helping households in poor countries to cope contemporaneously with extreme temperatures. As such, we demonstrate that social protection programs such as MNREGA reduce the temperature sensitivity of poor households, providing benefits that have previously received little consideration (204). In doing so, we identify an important policy instrument for adaptation, especially in developing countries where the rural poor are often unable to smooth consumption over district-level aggregate weather shocks.

Given the importance of agriculture in developing countries and with short-run weather risk – e.g., due to extreme events like heat waves – widely projected to grow in the years ahead due to climate change, it is crucial to know how well and quickly farmers in low-income countries adjust to exogenous temperature shocks to production. This question has interested development and agricultural economists for decades, at least since Schultz (1964), Antle (1983) and Fafchamps (1993) (21; 152; 350). More recently, environmental economists have begun to explore this issue, recognizing that agricultural damages induced by global warming may be especially problematic for farmers in low-income countries who rely on traditional methods for weather forecasting and may be unable to detect a change in temperature or to respond promptly even to changes they notice, for example due to binding financial liquidity constraints. But if farmers indeed detect and quickly adjust to warming temperatures on their own, the resulting damages could be contained. Therefore, understanding how and how fast farmers adapt to temperature shocks can usefully inform allocation of scarce public resources to build resilience and avoid permanent damage.

In my fourth chapter (Jagnani, Barrett, Liu and You 2019), I use household-level panel data from maize farmers in Kenya, and temperature data disaggregated across different stages of the crop growth cycle, to investigate if and how farmers adjust agricultural inputs in response to within-season temperature variation. We show farmers expressly identify warmer temperatures as a threat to maize productivity due to greater incidence of pests, weeds and crop diseases. And they undertake defensive investments quickly in response to short-run temperature shocks. They increase pesticide use in response to heat-induced increased biotic stress from diseases and pests that are most effectively addressed soon after emergence, early in the season. And farmers increase weeding effort throughout the season in response to higher temperatures that promote weed growth. Meanwhile, farmers reduce inorganic fertilizer use early in the growing season, contemporaneously with increased pesticide use. That could be a response to increased yield risk or binding financial liquidity constraints inducing trade-offs among input expenditures, or both. Overall, our results are consistent with a model in which farmers make production decisions sequentially, promptly adjusting to new information as it arrives within season, subject to financial constraints. Back of the envelope estimate indicate within-season adaptations undertaken by the average maize farmer in response to an extra degree day over 8C protected roughly 75% of expected yield loss.

Several papers have examined the extent of adaptation rather than how farmers adjust to warming temperatures (71; 119; 127; 128; 268; 343; 345; 375). However, among these only (375) examines agricultural adaptation in a developing country, India. Few studies have also examined how farmers adjust to higher than normal temperatures in developing countries (236; 237; 238; 353). These papers typically rely on cross-sectional variation to compare longer-run outcomes such as irrigation and crop choice in hot versus cold areas. While the cross-sectional approach approximates the ideal climate change experiment, omitted variables concerns in this approach mean that the average climate could be correlated with other fixed, unobserved factors. In this paper, we exploit plausibly exogenous short-run variation in weather to examine within-season adjustments in agricultural inputs. If farmers promptly adapt input applications within season in response to warmer temperature that differentially affect crop growth across different stages in the agricultural cycle – both directly through plant physiological effects of temperature and indirectly through temperature-induced changes in the supporting agroecology – then any analyses based on seasonal or annual temperature variation may miss important behavioral responses in the short-run. Moreover, if farmers can adjust in the short run, it is more plausible that they will also be able to adjust in the long run using methods unavailable to them in the short run (339) . Lastly, this literature has also overlooked farmer defensive investments arising not due to heat stress but rather due to biotic stresses arising from broader agroecological response to warmer weather. To our knowledge, this is the first economics study to isolate this mechanism behind farmer adaptation to temperature.

The share of the world's population in extreme poverty living on less than $1.90 a day has plummeted from 42 percent in 1981 to 10 percent in 2015 (402).

And yet, for most poor countries there is >90% likelihood that per capita GDP is lower today than if global warming had not occurred (133). In addition, fixed features of the natural environment (e.g., latitude, distance from coast, elevation) have had considerable influence on the geographic distribution of economic development (162; 291). Historically, human capital accumulation has been the primary channel through which people escape poverty (115). Today, 800 million people live in extreme poverty and an additional 1.2 billion people live on less than \$3.10 a day (402). In such a context "Essays on Human Capital, Environment, and Development" offers new empirical insights on the coupled dynamics of environmental and human outcomes and identifies new policy options to improve educational outcomes in developing countries.

Chapter 2

The Effects of Elite Public Colleges on Primary and Secondary Schooling Markets in India

2.1 Introduction

While educational attainment has long been linked to economic development, both as a driver of economic growth and a means to reduce income inequality (41), a complex debate surrounds the magnitude of public investments directed towards different levels of education. Investments in primary education are less politically contentious, as primary education is perceived to be a broad public good with few distributional issues, while public investments in higher education are decried as an income transfer to the elites, magnifying income inequality (348). International donors have long argued that public investments in universities and colleges bring in meager returns compared to investments in primary or secondary schools (56; 321; 401). Such analyses, however, ignore any potential developmental 'spillovers' of higher education investments. More specifically, if public investments in higher education increase lower levels of schooling, strengthening the entire education system, policymakers should account for these benefits and reevaluate the social returns to investments in higher education. To this end, in this paper we use the roll-out of elite public colleges in India to present the first estimates of such spillover effects of public investment in higher education on local markets for primary and secondary education, study the various channels that determine these consequences, and interpret our results through the lens of the literature on school entry and school choice.

India has the world's largest number of 5 to 24-year-olds, with roughly 500 million young people, and while primary and secondary school enrollment in India is over 95% and 70% respectively, enrollment in higher education institutions is roughly 20% (90). It is perhaps unsurprising that public budgets for higher education have been steadily increasing to fund the expansion of colleges and universities, and maintain pace with increases in educational attainment at the primary and secondary level: in 2016-17, almost two-thirds of the budget for school education and literacy was allocated to higher education (69). However, observers in the popular press have criticized these increases in higher education investments as inordinate, and expenditures on colleges and universities are perceived to come at the expense of schooling infrastructure.[1] Such observations may seem simplistic if higher education investments in turn facilitate the

[1]See for instance: (284; 383; 397; 400)

expansion of primary and secondary education. For instance, access to higher education may increase the demand for lower levels of education by raising parental aspirations. Simultaneously, higher education institutions may crowd-in public expenditure on other services like power, roads and water, and in turn facilitate private investment in primary and secondary education.[2] However, if higher education institutions are coupled with public investment in primary and secondary schools, public schools may crowd-out private investment in education.[3]

To measure the causal effect of public investment in higher education on local schooling markets we use the staggered rollout of elite public colleges in India at the district level between 2004 and 2014 in an event study framework (e.g., (28)).[45] Our event-study framework allows us to make fewer assumptions than a traditional difference-in-differences design. First, we do not compare districts that received an elite public college to plausibly dissimilar districts that did not receive these elite institutions. Instead, we restrict the sample to districts that eventually received an elite public college between 2004 and 2014. Second, unlike traditional difference-in-difference designs where the 'treatment' is rolled out in one specific year, the staggered rollout of elite public colleges al-

[2]The public finance literature studies crowd-out (106). If public capital reduces the cost of production for private capital, it is possible for public investments to crowd-in private capital (23; 24).

[3]We use 'school' to denote institutions imparting primary or secondary education, while 'colleges' or 'universities' are used to denote higher education institutions.

[4]Districts are administrative units within a state, and are a second-level administrative division (after states). India has 29 states and roughly 600 districts.

[5]In line with the larger trend of increased public spending on higher education, almost half of all elite public colleges were established countrywide over the last decade. These elite institutions are established and funded by the federal government and specialize in offering undergraduate or post-graduate education in one of the following fields of study: medicine (All India Institute of Medical Sciences - AIIMS), information technology (Indian Institute of Information Technology - IIIT), sciences (Indian Institute of Science Education and Research - IISER; National Institute of Pharmaceutical Education and Research - NIPER), engineering (Indian Institute of Technology - IIT; National Institute of Technology - NIT), architecture (School of Planning and Architecture - SPA) or business (Indian Institute of Management - IIM).

lows us to study the effects of elite college entry free of coincident changes in one particular year. Moreover, we employ year fixed effects to control for year-specific unobservables common across all districts, and district fixed effects to control for time-invariant unobserved characteristics that affect local education markets. In sum, our event study design allows us to identify impacts of elite public colleges by examining within-district changes in primary and secondary schooling outcomes that correspond to the year of elite public college entry specific to that very district. Importantly, our set up allows us to test for preexisting trends and the dynamic longer term effects after entry of elite public colleges.

We use three nationally representative education data sets: the National Sample Survey (NSS), the Annual Status of Education Report (ASER) and the District Information System for Education (DISE). We use all available rounds of the NSS data set over our period of analysis (these are 2004, 2007, 2010 and 2012), to examine the effects on educational attainment for primary- and secondary school-age children at the district level. We use annual data from ASER and DISE to evaluate the effects of elite public colleges on public vs. private enrollment (2006-2014) as well as the impacts on the number of public vs. private schools (2004-2014).

We present three key results. First, the establishment of a new elite public college increased years of education by 0.3 years among school-age children at the district level. Correspondingly, new elite public colleges led to significant increases in educational attainment at the primary, middle, secondary and higher secondary level.[6] Second, elite public colleges increased the probability of pri-

[6]Primary school ranges from grade 1 to grade 5, middle or upper-primary school ranges from grade 6 to grade 8, secondary school comprises of grade 9 and grade 10, higher secondary school includes grade 11 and grade 12. Tertiary or higher education includes undergraduate and post-graduate education or grade 13 and above.

vate school enrollment by 15%, while decreasing the probability of enrollment in public schools by 9%. Third, elite public colleges increased the number of private schools at the district level by 20%, but had no impact on the number of public schools. Moreover, we find that gains in educational attainment were driven by children staying in school longer as elite public colleges decreased dropouts in primary school. Overall, these findings suggest that private schools entered districts with new elite public colleges, students switched from public to private schools, and stayed in school longer.

There exist two key challenges for our identification strategy. First, public investment in higher education may anticipate changes in local schooling markets rather than causing it. Second, the precise timing of entry in each particular location of these elite colleges may be correlated with unobserved determinants of primary and secondary markets for education that are changing, concurrently driving both the location of elite public colleges as well as changes in the local education sector (for instance, industrialization). However, such changes happen gradually, and the existence of these confounding effects will be evident in the form of preexisting trends. If elite public colleges were introduced in places where children are staying in school longer, or if industrialization was the driving force, we would expect to see evidence of a positive pre-trend. Instead, the following pattern is visible across all our results: no pre-trends in our outcome variables followed by a sharp and statistically significant change in the year of elite public college entry. Moreover, a key feature of elite public colleges is that student admissions into these institutions are determined by extremely competitive nationwide entrance exams, and students enroll from all over the country. Therefore, there is little reason to believe that the precise timing of entry of these colleges is driven by coincident changes in local schooling markets.

Our results are also immune to other robustness and falsification tests supporting the validity of our baseline empirical specification. For instance, we run falsification tests by randomly re-assigning the year of entry of elite colleges among districts that ever received an elite public college and re-estimating our event study specification. Inspection of the resulting distribution of point estimates indicate that less than 5% of these estimates are larger in magnitude than the actual coefficient. Together, the only remaining threat to a causal interpretation of our estimates is if the specific year of entry of elite public college for each district systematically coincides with the timing of unrelated shocks, that have no observable pre-trends, but are correlated with the education market for that district. We believe that plausible omitted variables are unlikely to have all these properties and therefore propose that our baseline estimates are unbiased.

Our analysis of potential mechanisms that may be driving these effects of elite public colleges are informed by reports in the popular press that indicate that elite public colleges can transform a district into an educational hub, and crowd in public investments in other infrastructure services like roads, electricity and water. Indeed, we find compelling evidence that elite public colleges led to focal investments in infrastructure services at the village level, and may be one mechanism driving our results.[7] We use the precise latitude-longitude coordinates of elite public colleges, and Census Village Directories from 1991, 2001 and 2011, to show that even within-districts the decrease in distance to the closest elite public college, due to the entry of new elite public colleges across the country between 2001 and 2011, led to a significant increase in access to electricity, roads and water services at the village level. Moreover, these effects were larger for villages brought closest to a new elite public college. This is precisely

[7]Villages are the lowest level of subdivision in India after blocks, which are followed by districts and states, respectively.

what one would expect if elite public colleges led to focal investments in other public infrastructure services for villages closest to the new elite public college. As a falsification test, we estimate the effects of changes in distance to elite public college between 2001 and 2011 on the change in access to roads, water and electricity between 1991 and 2001. As expected, we find that future changes in distance to the elite college do not predict current infrastructure investments.

We further corroborate these effects using annual, satellite-measured nighttime lights data between 2004 and 2012 as a proxy for electrification, and show that an increase in proximity to elite public colleges led to corresponding increases in village level nighttime lights intensity. We include both village and year fixed effects, and examine the year-by-year change in distance between a village and nearest college in a semi-parametric manner. Similar to the results observed using Census Village Directories, we find that the effects of elite public colleges on changes in nighttime light intensity decreased with an increase in the changed distance to the nearest elite public college. It is plausible that conditional on the availability of higher education institutions, such investments in public infrastructure reduced setup costs for private schools, and consequently, the entry of private schools decreased travel costs for marginal students, enabling them to get additional years of education. Using the 2004 and 2011 rounds of Indian Human Development Survey (IHDS), we find that elite colleges decreased the distance traveled to the nearest private school at the household level.

Our findings are consistent with previous evidence that shows that private schools in India are more likely to be present in villages with access to public infrastructure (235; 302), and the literature on school choice in developing countries that indicates that distance to school is a central determinant to school choice in low income countries (84). Indeed, (13) find that lowering distance increased enrollment in private schools in Pakistan, partly by transfers from public schools.

We explore various additional mechanisms that might be driving the effects of elite public colleges on schooling markets. For instance, it is plausible that colleges increase local populations due to an influx of children of faculty. Similarly, colleges may create new employment and increase local incomes, raise parental aspirations, help overcome the lack of information, or increase actual or perceived returns to education. Although we fail to find evidence that increases in local population or income are driving these effects, we can not completely rule out these channels. Similarly, we can not completely rule out demand externalities such as changes in parental aspirations, or effects on actual or perceived returns to education, as possible explanations for our finding, and consider them to be plausible complementary channels.[8]

The rest of the paper is organized as follows. In Section 2.2 we provide a brief literature review. Section 2.3 gives background information on elite public colleges in India. In Section 2.4 we provide a theoretical model of school choice and private school entry to understand the underlying possible mechanisms. Section 2.5 describes the data. In Section 2.6 we investigate the impacts of elite public colleges on educational attainment, enrollment in both public and private schools, and the number of primary and secondary schools. We discuss potential mechanisms behind these empirical patterns in Section 2.7, and Section 2.8 concludes.

[8]As we observe immediate effects on local schooling markets, it is likely that such demand externalities are partly responsible for our results.

2.2 Contributions to the Literature

If higher education institutions are a policy tool for economic development, knowledge about the precise channels through which universities bring about development impacts will help identify optimal locations for higher education investments. Existing evidence, almost exclusively from affluent countries, suggests that investment in higher education generates long-term local effects through *direct* increases in the supply of human capital and greater innovation.[9] However, such mechanisms may be less relevant for lower-income countries.[10] We show that higher education institutions facilitate educational attainment among school-age children in India, *indirectly* increasing the supply of human capital. In India, over 80 million children are out of school (90). Thus, optimally targeted higher education investments may strengthen both the foundations of the education system (i.e., primary and secondary school), as well as tertiary education, since lower levels of schooling are critical as prerequisites for higher education.

We also contribute to the literature on place-based policies that target infrastructure investment towards underdeveloped regions.[11] A small number of papers within this literature have studied place-based programs in developing countries (305; 322; 359). Here we present the first estimates of the developmental impacts of college infrastructure in a lower-income country. Our findings

[9] See for instance: (2; 3; 18; 19; 50; 81; 193; 218; 219; 225; 405; 409).

[10] For instance, higher education institutions in India are quite small in relation to the size of the local population, as average enrollment is just over 700 students (178), so benefits to the local economy from increases in human capital endowment might not be substantial. Also, research is not the primary mandate of higher education institutions in India, and they lag significantly behind universities in high- and middle-income countries in terms of research output. See: (212; 382; 399).

[11] See (288) for a review on the literature examining the economic effects of place-based policies.

suggest that place-based policies that involve the construction of elite public colleges in India may have larger effects on provision of public goods than certain last-mile programs that target specific infrastructure services. We find that elite public colleges increased nighttime brightness by 0.5 units at the village level. In comparison, a rural electrification program in India that provided electricity access to hitherto unconnected villages increased nighttime brightness by only 0.15 units (75). Our estimates are comparable to a policy that targeted massive improvements in public infrastructure, a generous investment subsidy and a complete exemption from corporate and excise taxes for a newly formed state in India (359).[12] In India, access to public goods like electricity, roads, water and education is a matter of who can extract them from the political system (33). For instance, even Special Economic Zones in India have failed to crowd-in public expenditure on services like power, roads and water (14). In such a context, not only do elite public colleges lead to significant investments in other public goods, but also crowd-in private investment in education.

2.3 Elite Public Colleges

As of 2011, India's Universities Grant Commission lists 42 central universities, 275 state universities, 130 deemed universities, 90 private universities, and 93 Institutes of National Importance (hereinafter referred to as elite public colleges). The federal government establishes and funds all elite public colleges.

[12]A possible interpretation of our results could be that a suite of focal infrastructure investments may have larger development impacts than certain last mile programs that target specific infrastructure services. For instance, (75) find that a rural electrification program in India had no effects on educational attainment, while (8) find that a rural road construction program in India increased middle school completion by 7%. In comparison, we find that elite public colleges increased middle school completion by 14%.

These elite colleges specialize in both undergraduate and post-graduate education in technical fields like medicine, information technology, sciences, engineering, architecture or business – most famously the Indian Institutes of Technology (IITs) and Management (IIMs). Importantly, they share certain unique features that are useful in investigating the causal effects of higher education investments on lower levels of schooling and understanding the underlying mechanisms.

First, student admission into these institutions are determined by extremely competitive nationwide entrance tests. For instance, any student who wants to gain admission into any elite medical college–AIIMS–is required to appear for a common, nationwide AIIMS entrance exam. Importantly, this means that all elite public colleges in a particular field of study are drawing applicants from the same national pool.[13] Thus, the market for students at elite public colleges are national.[14] Second, the location of newer elite colleges is a function of addressing regional imbalance caused by location of older such institutions.[15] For instance, a state is unlikely to get a new elite public college in medicine if an elite medical college already exists within the state boundaries.[16] However, within a state, the location of elite public colleges is often determined through discus-

[13]Except for the National Institutes of Technology or NITs, which reserve 50% seats for state students, other elite public institutions have no such reservation policy for local state students. Our results are robust to dropping these elite public colleges from the sample. However, every higher education institution in India has to reserve 15%, 7.5% and 28% seats for candidates from the 'Scheduled Caste', 'Scheduled Tribe' and 'Other Backward Classes', respectively.

[14]For instance, students residing in roughly half of all PIN codes in India appeared for the 2009 entrance exam for admission into 15 Indian Institute of Technology - IITs. See: (393; 394; 395) for media reports. Similarly, students across the country appear for national entrance exams that determine admission into elite public colleges in other fields of study. The market for faculty at elite public colleges are national as well. In fact, new elite public colleges have successfully attracted young faculty educated in top institutions in India and abroad (See: (381)).

[15]See: (110; 384; 386).

[16]We examine if states with an elite public college in a certain field of study, before 2004, received a new elite college in the same field of study, between 2004 and 2014. We find no such instance (Figure A.1).

sions between the federal and state government. While this means that such colleges are not placed randomly, since admissions are determined by competitive countrywide exams, the year of entry at a certain district is unlikely to be driven by anticipated changes in local schooling markets. We restrict our analysis to districts that received an elite public college between 2004 and 2014, ensuring that we are not comparing dissimilar districts, and include district fixed effects to adjust for level differences across districts. Thus, we identify impacts of elite public colleges by examining within-district changes in primary and secondary schooling outcomes that correspond to the year of elite public college entry specific to that district.

Lastly, discussions between administrators, covered extensively by the popular press, help inform our analysis of the potential mechanisms through which elite public colleges effect primary and secondary schooling markets. For instance, local administrators believe that elite public colleges can transform a district into an educational hub and encourage economic activity. Thus, while the federal government has pushed for districts with good transportation and other infrastructure services as it is easier to attract faculty and students to economically developed districts, state administrators often lobby the federal government to procure these elite institutions for underdeveloped districts.[17] Indeed, anecdotal evidence suggests that newer elite public colleges have indeed been established in underdeveloped districts, unlike their older counterparts. In such districts it is therefore plausible that these institutions lead to focal public investments in infrastructure services like roads, electricity and water, if both the federal and state government want to safeguard returns from such higher education investments.

[17] See: (159; 389; 391; 396; 398).

Quotes from the foundation stone laying ceremony of an elite business school in an underdeveloped state of India, Jharkhand, are a case in point.[18] Some capture the sentiment of locals: *"A nondescript village devoid of proper electricity and drinking water supply, Cheri (village) has one single kutcha (temporary) road that links it to Ring Road that leads to Ranchi (capital of Jharkhand). However, with today's high-profile installation, its residents hoped of good tidings in the future."* Others, capture the expectations of the Minister for Rural Development: *"Such institutions in backward regions like Jharkhand are beneficial."*

Table 2.1 provides year-on-year changes in the number of districts with elite public colleges between 2004-2014, and Figure A.2 shows districts where elite public colleges were setup between 2004-2014, and used in our analysis. We leverage 26 (treatment) districts, spread across 22 states, that did not have an elite public college prior to 2004, and only received one between 2004-2014, to identify the effects of public investment in higher education on lower levels of schooling.[19]

2.4 Theoretical Framework

In this section, we present a conceptual framework of household school choice and private-school entry and determine the equilibrium in local markets for primary and secondary education. To help guide our empirical analyses, we allow elite public colleges to disrupt this equilibrium and highlight the mechanisms through which elite public colleges may affect primary and secondary school-

[18] See: (388; 390).

[19] In robustness checks we rule out the possibility that a single treatment district or single treatment year is driving our results, and cluster-bootstrap standard errors following (80).

ing. Details are in Appendix A.1.

2.4.1 Setting: Market for Primary and Secondary Schooling

The supply of public schools is determined exogenously by district administrators. The supply of private schools, however, is market determined; they enter if they can earn positive profits.[20] Private schools are profit maximizers, have heterogeneous costs/efficiency (235), and are price takers in a competitive market, charging p.[21]

Total educational output (in student-years) of school j with inputs X_j, is $Q_j = \bar{\theta}X_j$, and the school's cost function $Z(X_j) = z_{1j}X_j + \frac{1}{2}z_2X_j^2$ is quadratic.[22] $\bar{\theta}$ is the average education level in the district and captures demand externalities driven by aspirations and peer effects (55; 61) that may be associated with proximity to elite public colleges. z_{1j} reflects the heterogeneity in costs across schools and districts, drawn from a distribution that varies across districts given their infrastructure. The total number of potential private schools is N, and only schools that make a positive profit enter the district. In Appendix A.1, we show profit maximization implies the total supply of private schooling is:

$$Q_{Sy} = \sum_{j=1}^{N_1} Q_j = \sum_{j=1}^{N_1} \bar{\theta}\frac{p\bar{\theta} - z_{1j}}{z_2} = \frac{p\bar{\theta}^2 N}{z_2}(p\bar{\theta} - \overline{z_1}) \tag{2.1}$$

[20]For notational convenience we drop the district sub-script from our equations, even though quantities vary across districts.

[21](281), find that children enrolled in private schools do not perform better than their peers in public schools on subjects taught in both schools, although private schools are more cost-effective. Our specification reflects these points – private schools have the same output as public schools (an assumption easily relaxed without a change in comparative statics), although the operating costs are different.

[22]It is easy to hire the first few teachers, it is more costly to hire the next as the pool dwindles.

Demand for schooling depends on the costs of going to school and the returns to schooling. Costs c_{ij} vary across individuals based on tuition p, travel costs to the nearest school(s) T_{ij}, ability Δ_i and wealth W_i: $c_{ij} = \alpha p + \beta T_{ij} - \gamma ln(W_i) - \Delta_i$.

Children will attend school if the returns to education, r, are greater than the costs. In Appendix A.1 we show, for N_0 number of public schools, and a student population the size of M, the aggregate demand for private schools is:

$$Q_d = MN_1 F(\phi - \alpha p)[1 - F(\phi)]^{N_0}[1 - F(\phi - \alpha p)]^{N_1 - 1} , \tag{2.2}$$

where ϕ is a function of the returns to education, travel costs, wealth, and ability, and the idiosyncratic components of the cost function are drawn iid from $F(.)$.

2.4.2 Comparative Statics: Entry of Elite Public College

This set up allows us to deduce the equilibrium, and examine the effects of elite public colleges on the supply Q_{Sy} and demand Q_d for private schooling at the district level.[23]

Effects of Infrastructure Upgrades: If elite public colleges lead to investments in water, roads and electricity, it may reduce entry costs, and cause an outward shift in the supply of private schools ($dQ_{Sy}/d\overline{z_1}|_p < 0$; $dQ_{Sy}/dz_2|_p < 0$). Increases in the supply of private schools lowers the equilibrium tuition charged at a private school ($dp/d\overline{z_1} > 0$; $dp/dz_2 > 0$) and the distance to the nearest private school (lower T_{ij}). Lower distances, in turn, will increase the demand for

[23]Detailed derivations are in Appendix A.1.

private schooling ($dQ_d/dT_{ij} < 0$). If elite public colleges increase the number of private schools by lowering setup costs, it may increase private schooling, and educational attainment.

Effects of Changes in Income, Population, and Aspirations: Increases in income ($dp/dln(w) > 0$; $dN_1/dln(w) > 0$), population ($dp/dM > 0$; $dN_1/dM > 0$), a rightward shift in student's ability distribution ($dp/d\delta > 0$; $dN_1/d\delta > 0$), increases in actual or perceived returns to education ($dp/dr > 0$; $dN_1/dr > 0$) or increases in educational aspirations ($dp/d\bar{\theta} > 0$; $dN_1/d\bar{\theta} > 0$) will increase the demand for all schooling (both public and private), as well increase the equilibrium tuition and the number of private schools. New elite public colleges, may therefore, increase the demand for all schooling through any of these mechanisms. Our theoretical framework, therefore, generates the likely candidates for the mechanisms that we explore in our empirical exercise.

2.5 Data

2.5.1 National Sample Survey

The National Sample Survey (NSS) is a nationally representative survey consisting of yearly small sample rounds ('thin' rounds), and five yearly large sample rounds ('thick' rounds). These surveys ask detailed questions about different levels of education and contain extensive information on schooling outcomes including years of education and educational attainment. The probability-weighted sample is constructed using a two-staged stratified sampling procedure with the first stage comprising of villages and block, and the second stage consisting of households. Households are selected systematically with equal probability, with a random start. We use four different rounds of the NSS data, between 2004 and 2012. The 2004 and 2010 'thick' rounds are the large sample rounds. The 2007 and 2012 are small sample 'thin' rounds. Using these four NSS rounds, we evaluate the impact of elite public colleges on years of schooling and educational attainment. We present summary statistics on years of schooling and educational attainment in Table A.1.

2.5.2 Annual Status of Education Report

The Annual Status of Education Report (ASER) is an yearly education survey for school-age children in India. The sample is a representative repeated cross section at the district level.[24] The survey contains information on enrollment status, current grade and school type for every child in the sampled household. Children are also tested in math and reading ability. The ASER is useful for our analysis for multiple reasons. First, ASER provides national coverage and a large sample size for each district. Second, unlike schools-based data, it is not administered in schools and therefore covers children both in and out of school. Third, it is administered each year on 2 to 3 weekends from the end of September to the end of November limiting considerations of spatially systematic seasonality in data collection, and endogenous sampling as in school children are likely not available on weekdays. We use nine rounds of the ASER data between 2006 and 2014 to examine the effects of elite public colleges on private vs. public school enrollment. We present summary statistics on private

[24] In each district, 30 villages are sampled from the Census 2001 village list. In each village, 20 households are randomly sampled. This gives a total of 600 sampled households in each rural district, or about 300,000 households at the all India level.

and public enrollment in Tables A.2 and A.3.

2.5.3 District Information System for Education

District Information System for Education (DISE) is an administrative dataset on primary schools in India. Data collection involves a census of all schools in India, is coordinated at the district level, and then aggregated by states. Annual district level statistics across the country are made publicly available in the form of 'District Report Cards'. These data are designed to reflect statistics as of September 30 of the school year, which starts in July. We use eleven rounds of DISE data between 2004 and 2014 to examine the effects of elite colleges on the number of private and public schools. Although, DISE data only provide statistics on primary schools, these include primary schools offering post-primary education. We present summary statistics on number of private and public schools in Tables A.4 and A.5.

2.6 Effects on Lower Levels of Schooling

2.6.1 Years of Schooling and Educational Attainment

Using NSS data for individuals between 6 and 20 years of age, we estimate Equation 2.3 to evaluate the impact of elite public colleges on years of schooling and educational attainment. Our empirical strategy exploits variation in the timing of establishment of elite public colleges in districts that received an elite public college between 2005 and 2011 in an event study framework (e.g., (28)). We estimate the following model:

$$y_{ijt} = \sum_{\tau=-p}^{-2} \beta_\tau 1(t - T_j^* = \tau) + \sum_{\tau=0}^{m} \beta_\tau 1(t - T_j^* = \tau) + \mu_j + \chi_t + \epsilon_{ijt} \tag{2.3}$$

where y_{ijt} is the outcome of interest for child i in district j in year t.[25] Estimates characterizing the effects of elite colleges are the coefficients on the event year dummies, $1(t - T_j^* = \tau)$, which are equal to 1 when the year of observation is τ rounds away from T_j^*, the year when the elite college was established in district j ($\tau = -1$ is omitted). These estimates are average treatment effects of elite public colleges relative to the round before elite public colleges were established, $\tau = -1$.[26] For instance, if an elite public college was established in 2008 in a district j, the 2004 and 2007 rounds capture the pre-period $\tau < 0$, whereas the 2010 and 2012 rounds capture the post-treatment period $\tau \geq 0$. μ_j indicate district level fixed effects, while χ_t stands for survey-round indicators. We restrict our sample to districts that ever received an elite college so that we do not compare estimates to dissimilar districts. By adding district fixed effects μ_j, we control for time-invariant unobserved characteristics that affect local education markets and may also be correlated with the presence of elite public colleges. Round indicators control for round-specific unobservables common across all districts.

[25] Since the NSS data is collected with time gaps, τ denotes number of survey rounds for the NSS data, where t = 2004, 2007, 2010, 2012. Therefore, as a robustness check we report estimates separately by event year (Figures A.3 and A.4). It is reassuring that these results are quantitatively similar to our baseline estimates. However, because we observe 4 NSS survey rounds between 2004-2012, each event year only includes a few treatment districts. For instance, $\tau = 0$ only includes districts where an elite public college was introduced in 2007 and 2010. Therefore, we prefer our baseline specification. Note that for the ASER and DISE data sets, which are collected annually, τ denotes number of years.

[26] We expect to observe effects of elite public colleges somewhat concurrently. That is, the causal impact of elite public colleges is identified from the change in our outcomes of interest in the first observable round of data after entry of these institutions ($\tau = 0$). Thus, $\tau = -1$ is the natural baseline to capture these effects.

Thus, we identify impacts of elite public colleges by examining within-district changes in primary and secondary schooling outcomes that correspond to the year of elite public college entry specific to that district. This approach allows us to make fewer assumptions than a traditional difference-in-differences design as we do not include any districts that never receive a college (which are likely to be rather different), and there is no longer just one particular year that affects all treated districts (which may be correlated with other year-specific shocks).

Two challenges remain for our identification strategy. First, the location and precise timing of entry of elite public colleges may be correlated with unobserved determinants of the primary, middle and secondary markets for education that are changing continuously, and concurrently driving entry of elite public colleges. Second, public investment in tertiary education may anticipate changes in local schooling markets rather than causing it. Since student admissions to elite colleges are determined by highly competitive nation-wide entrance exams, and students enroll from all over the country, there is no reason to believe that the establishment of these colleges is driven by anticipated future changes in local schooling markets. The more relevant concern is whether the timing of public college entry is correlated with preexisting trends in education markets. As most changes are gradual, the existence of confounding effects, if present, will be evident in the form of preexisting trends.

Using Equation 2.3, we investigate impacts on years of schooling, as well as completing primary school (Grades 1-5), middle or upper-primary school (Grades 6-8), secondary school (Grades 9-10) and higher secondary school (Grades 11-12). Figure 2.1 presents the estimates for years of schooling. We find that the coefficients for the treatment rounds are positive and statistically significant. Elite public colleges increased schooling by over 0.3 years in the short-run ($\tau = 0$), and by 0.8 years in the longer-run ($\tau = 1$).[27]

Next, we examine the effects on educational attainment. We find that elite public colleges increased educational attainment at each schooling level (Figure 2.2). Colleges increased primary and middle school attainment by 5 percentage points (8% and 14%, respectively) in the short-run, and 10 percentage points (17% and 30%, respectively) in the longer-run . Secondary and higher secondary attainment increased by roughly 2 percentage points (13% and 40%, respectively) in the short-run, and 5 percentage points (30% and 100%, respectively) in the longer-run.

We find no evidence of preexisting trends, and instead detect a statistically significant change in the years of education that coincides with the first round following the establishment of the college, $\tau = 0$. If elite public colleges were introduced in places where children are staying in school longer, or if rapid industrialization was driving the timing of elite public college entry as well as changes in the local schooling market, we would expect to see evidence of a positive pre-trend. Now, the only remaining threat to a causal interpretation of our estimates is if the specific year of entry of elite public college for each district systematically coincides with the timing of unrelated shocks, that have no observable pre-trends, but are correlated with the education market for that district. We believe that plausible omitted variables are unlikely to have all these properties and therefore conclude that our baseline estimates are unbiased.

In other robustness checks, we estimate the effects of elite public colleges on children's enrollment status (Figure A.5). As one might expect, we find sug-

[27]Here, $\tau = 1$ denotes 3 to 4 years after the entry of elite public college.

gestive evidence entry of elite public colleges increases school enrollment. We estimate the effects on years of schooling and educational attainment for individuals that were too old to change their education decisions – individuals between 21 and 65 years of age – as a falsification test (Figures A.6 and A.7). Next, we control for children's age, and find that our estimates remain unaffected (Figures A.8 and A.9). We show that the effects on years of schooling are robust to restricting the sample to older children (Table A.10), and that the attainment results are robust to restricting estimation for each tier of education – primary, middle, secondary and higher secondary – to the corresponding age-appropriate sample (Figure A.11). We also show that the effects on years of schooling and educational attainment are robust to restricting the sample to younger children (Tables A.12 and A.13). Since our sample consists of only districts that ever received a college, it is possible that a single outlier may drive our results. Therefore, we drop each district, one at a time, estimating Equation 2.3 each time (Figures A.14 and A.15). In addition, we drop all districts where elite public colleges were introduced in a single year, one year at a time (Figures A.16 and A.17). We find that these estimates are not driven by a single district or treatment year. Lastly, we cluster-bootstrap our standard errors following (80) (Table A.6). Our estimates remain precisely estimated.

2.6.2 Private vs. Public Enrollment

Next, we investigate the effects of elite colleges on private vs. public enrollment for children in Grades 1-10 (5-16 year olds). We employ an event study framework, estimating Equation 2.3, but now use the *annual* ASER data set. Here too, we restrict our sample to districts that ever received an elite college so that we do not compare dissimilar districts.

In Figure 2.3 we report the impact of elite public colleges on private and public school enrollment. For public school enrollment, the coefficient in the year of treatment (τ = 0), the year when elite public colleges were established, is -0.05, which means that public colleges led to a 5 percentage point (8%) decrease in the probability of public school enrollment. These effects get larger in the longer-run or 4 years after the entry of an elite public colleges (τ = 4). In contrast, elite public colleges are associated with an increase of 5 percentage points (20%) in the probability of private school enrollment in the year of treatment, and of over 10 percentage points (40%) by τ = 4. We find no evidence of a preexisting trends in any of our estimates. Indeed, the trend break in the left-hand side variable at τ = 0 is apparent, as well as economically and statistically significant for both public and private enrollment. The estimates of the pre-treatment periods are small in magnitude and statistically indistinguishable from zero.

In robustness checks we control for district-specific trends, age, and gender; our estimates remain relatively unchanged (Figure A.18). Next, we drop each treatment district, one at a time, estimating Equation 2.3 every time (Figure A.19). In addition, we drop all districts where elite public colleges were introduced in a single year, one year at a time (Figure A.20). We find that these estimates are not driven by a single district or treatment year. We also conduct a placebo test where we run 200 iterations of Equation 2.3, by randomly assigning the year of treatment among treated districts for each iteration. Inspections of the resulting distribution of point estimates can help test the appropriateness of our statistical model and the likelihood that our results are an artifact of chance or of a systematic structure in the data. Indeed, the distribution of point estimates at $\tau = 0$ indicates that less than 5% of these estimates are larger in magnitude than the actual coefficient (Figures A.21 and A.22). Lastly, we cluster-bootstrap our standard errors following (80) (Table A.7). Our estimates remain precisely estimated.

The ASER data set also helps us investigate the pattern of gains in educational attainment observed using the NSS data set. In ASER, the proportion of children who never attended school at the baseline ($\tau = -1$) was less than 2 percent. It is plausible then, that gains in educational attainment were driven by children staying in school longer. Indeed, we find that the grade students dropped out of school increased by 0.5 at $\tau = 0$, and by almost 0.8 in the longer-run ($\tau = 4$). We also examine the effects of elite public colleges on dropouts in primary school (Grade 8). We find that elite public colleges decreased the probability of dropouts in primary school by 8 percentage points in the short-run ($\tau = 0$) and by over 20 percentage points in the longer-run among children who eventually dropped out of school (Figures A.23 and A.24).

2.6.3 Private Schools

Next, using the *annual*, district level DISE data set, we estimate Equation 2.3 and examine the impact of elite public colleges on the number of private schools. Here y_{jt} is the log of number of private schools in district j in year $t \in [2004, 2014]$

In Figure 2.4 we show the effects of elite public colleges on the number of private and public schools. Entry of elite public colleges led to a 20 percent increase in the number of private schools at $\tau = 0$ and a 30 percent increase by the fourth year ($\tau = 4$). Importantly, we find that elite colleges have no impact on the number of government schools, suggesting that the colleges did not lead to broader increases in public expenditure on education in treatment districts. In robustness checks we show that our results remain unaffected by the addition of district-specific linear trends (Figure A.25). Next, we drop each treated district, one at a time, estimating Equation 2.3 every time (Figures A.26). And drop all districts where elite public colleges were introduced in a single year, one year at a time (Figure A.27). Our estimates are not driven by a single district or treatment year. We also conduct a placebo test where we run 200 iterations of Equation 2.3, randomly assigning year of treatment among treated districts for each iteration. The magnitude of the effect presented in Figure 2.4, at $\tau = 0$, is observed in less than 5% iterations (Figure A.28). Lastly, we cluster-bootstrap our standard errors following (80) (Table A.8).[28]

2.7 Mechanisms

We find strong evidence that one mechanism responsible for the effects of elite public colleges on lower levels of schooling is infrastructure upgrades. We find that elite public colleges increased access to paved roads, electricity and tap water, and the intensity of these effects was largest among villages closest to the elite public college. While we find insufficient evidence in support of alternative channels, we can not rule them out.

[28]The DISE data also includes information of enrollment in primary and secondary school at the district level. Therefore, as a robustness check, we use DISE to corroborate the effects of elite public colleges on private vs. public school enrollment observed in the ASER data (Figure A.29). We find that the estimates are qualitatively similar. However, we prefer using the ASER data to estimate the effects on public vs. private school enrollment as questions have been raised about the veracity and trustworthiness of enrollment data from DISE (Page 15, (232)).

To fix ideas, consider a simple explanation. Elite public colleges led to infrastructure investments lowering the setup costs for private schools. New private schools enter the market and students who live closer to the private school transfer from public to private schools, staying enrolled in school for longer.

2.7.1 Public Infrastructure Investments

Comparative statistics from our model suggest that a decrease in entry costs for private schools shifts the supply curve out ($dQ_{Sy}/d\overline{z_1}|_p < 0$; $dQ_{Sy}/dz_2|_p < 0$). If elite colleges increase access to infrastructure, then this would lead to the entry of new private schools.

Census Village Directories

To find evidence for this prediction, we link infrastructure indicators from the 2001 and 2011 Census Village Directories to latitude-longitude coordinates of each village, as well as each elite public college.[29] Then, for each year we calculate the distance of every village in India to the closest elite college. We exploit the variation in distance to elite colleges at the village level, due to the entry of new colleges, and capture the difference in effect sizes for villages at varying distances from the new college. If elite colleges led to focal investments in public infrastructure, we should observe larger effects for villages where a new public college was established, but smaller effects for villages that were farther away. Thus, we use the *change* in distance of each village to the closest public

[29] We describe the data from Village Census Directories and Village Night Lights in Appendix A.3.1.

college between 2001 and 2011, due the entry of new elite colleges, and estimate the following semi-parametric model:

$$
\begin{aligned}
y_{ijt} = & \sum_{\tau=1}^{z} \alpha_\tau 1(DistancetoCollege \in [m, m+20])_{ij} + \beta\ Post_t \\
& + \sum_{\tau=1}^{z} \gamma_\tau 1(DistancetoCollege \in [m, m+20])_{ij} \times Post_t \quad + \mu_j + \epsilon_{ijt}
\end{aligned} \tag{2.4}
$$

where $m = 0, 20, ..., 60$ kms. y_{ijt} is the outcome of interest for village i in district j in year t. Estimates characterizing the effects of elite public colleges are captured by the vector of coefficients γ_τ. The variable $1(DistancetoCollege \in [m, m+20])_{ij} = 1$ if the distance of village i in district j has ever been between 0-20 kms, 20-40 kms, 40-60 kms, or 60-80 kms away from the closest elite public college, 0 otherwise. Variable $Post_t$ is a post-treatment year for being in Census year 2011. $1(80 <= DistancetoCollege)_{ij}$ is the omitted distance category. μ_j are district-level fixed effects.

We present these results in Figure 2.5. We find that elite public colleges increased access to infrastructure, and the effects on electricity (6 percentage points), water (8 percentage points) and roads (4 percentage points) were larger for villages closer to elite colleges than for villages farther away. As a placebo test, we examine the effects of future changes in distance to colleges on current changes in infrastructure. We estimate Equation 2.4 to evaluate the effects of changes in distance to colleges between 2001 and 2011 on changes in access to roads, water and electricity between 1991 and 2001. If villages closest to the colleges were targeted for investments in public infrastructure services and colleges were a consequence and not a cause of such a program, we would expect to see an association between future changes in distance and current infrastructure investments. However, Figure 2.5 indicates that future changes in distance (between 2001 and 2011) do not predict current infrastructure investments (between 1991 and 2001).[30]

Village Night Lights

Next, we estimate the effects of elite public colleges on village-level nighttime lights, as a proxy for rural electrification. Here too, we use latitude-longitude coordinates for each village and elite public college in India and calculate the distance of every village to the nearest elite college between 2004-2012. We estimate Equation 2.4 where y_{ijt} is now log mean nighttime lights in village i, district j, year t. Since we have 9 years of night lights data, we include village fixed effects (μ_i) and identify the effects from year-on-year changes in distance to elite public college on electrification at the village level. Furthermore, we estimate an even more flexible version of Equation 2.4, where we use 10km bins between 0 and 150kms, with $1(150 <= DistancetoCollege)_{ijt}$ being the omitted category. Our identifying assumption is that, conditional on village and year fixed effects, changes in the distance of villages to the closest elite college are not correlated with unobservable village specific, time-varying attributes that also affect changes in night time lights by distance bins.

Figure 2.6 presents the effects of elite public colleges on village night lights. The coefficient for $1(DistancetoCollege \in [0, 10]km)_{ijt}$ is 0.15, implying that villages within 10kms from the new college saw a 15 percent increase in mean

[30] In addition, there were at least two independent public infrastructure initiatives launched in the 2000s across India, Rajiv Gandhi Grameen Vidyutikaran Yojana (RGGVY) and Pradhan Mantri Gram Sadak Yojana (PMGSY). PMGSY was launched in 2000 while RGGVY was launched in 2005. Both programs were targeted to villages above a certain population cut-off, 1000 for PMGSY (8) and 300 for RGGVY (75). We examine if villages nearest to elite public colleges were more likely to meet the village level population cut off required to be eligible for these programs (Figure A.30). We fail to find evidence for a positive association between distance to the nearest elite college in 2011 and village-level population in 2001, suggesting that the location of elite public colleges and the increase in public infrastructure investments in nearby villages were not associated with these rural infrastructure initiatives.

night light intensity. Importantly, the effects of elite public colleges on changes in nighttime light intensity decreased with an increase in the changed distance to the nearest college.[31][32]

Public Infrastructure Investments and Private Schooling

In Section 2.6.3, we showed that elite public colleges increase the entry of private schools at the district level. Combined with our estimates on infrastructure indicators, we conclude that the entry of private schools is driven by infrastructure upgrades. Such a claim is backed by existing evidence: (235) and (302) find that private schools in India are more likely to be present in villages with access to public infrastructure. However, public schools are less likely to respond to such investments as governments may prioritize under-served regions (140; 235).

If infrastructure upgrades are driving the entry of private schools, effects on private school entry should be largest in villages closest to the elite public college, as the magnitude of the effects on public infrastructure are highest among villages closest to the elite public college. Using the 2011 Census Village Directory, we estimate Equation 2.4 to examine the correlation between the presence of elite public colleges and private schools in a cross-section with district fixed effects. Indeed, we find strong evidence that private schools are more likely to be present in villages closest to elite public colleges (Figure 2.7).

Last, we examine the effects of elite public colleges on the distance to pri-

[31]These effects are robust to the inclusion of state-by-year fixed effects where we control for all year-specific unobservables that vary by state as opposed to just year fixed effects that only control for year-specific unobservables common across India (Figure A.31).

[32]As a robustness check, in Figure A.32 we estimate equation 2.3 and show entry of elite public colleges led to a sharp and statistically significant increase in night lights intensity in villages within 10 kms from the new college.

vate schools. Distance is a central determinant of school choice in low income countries (84). For instance, (13) showed that lowering distance increased enrollment in private schools in Pakistan, partly by transfers from public schools. Using 2004-05 and 2011-12 rounds of the Indian Human Development Survey (IHDS), we evaluate the effect of elite public colleges on distance to school for children attending private school in treatment vs. control districts in a triple difference framework.[33] We find suggestive evidence that elite public colleges led to a decrease in distance to private schools (Table 2.2). More specifically, we find that the entry of elite public colleges between 2005 and 2011 increased the likelihood that private-school going children were attending schools less than 1 km away from home in treatment districts by 13 percentage points, compared to private-school going children in districts that did not receive an elite college between 2005 and 2011. The entry of private schools may have potentially solved a (travel) cost constraint for marginal students, enabling them to get additional years of education as they transfer from public to private schools.

2.7.2 Alternative Explanations

There exist other channels that could potentially explain the observed relationship between elite public colleges and lower levels of schooling. Specifically, we consider five alternative explanations: (1) population, (2) income, (3) aspirations or returns to education, (4) access to higher education and (5) powerful politicians. Using existing data sets, we find insufficient evidence for these alternative mechanisms, but can not conclusively rule them out.

[33] In Appendix A.3.3, we briefly describe the data set.

Population: $dp/dM > 0$ **;** $dN_1/dM > 0$

Demand for all schooling (both public and private) increases with population, in turn increasing equilibrium tuition, and the number of private schools. If elite public colleges increase local population by creating employment opportunities within the college, or newly created jobs in existing or new firms, it could increase the demand for all schooling and facilitate entry of private schools. However, we fail to find strong evidence for increases in population as an underlying mechanism.

First, if elite public colleges increase demand for schooling through the population channel, we would also see an increase in enrollment in public schools. However, we find a significant decline in public school enrollment. Second, using district level population data we examine the effects of elite public colleges on both total population and population by age group. We fail to find evidence for an increase in population of school-age children in districts that received an elite public college (Figure A.33).

Children of Faculty and Staff: $dp/d\delta > 0$ **;** $dN_1/d\delta > 0$ Next, we explore if children of faculty and staff alone can explain our results. A right-ward shift in the distribution of ability will increase the demand for all schooling, raise market price (tuition) and induce more private schools to enter the market. If children of faculty at these elite public colleges are more able, then elite public colleges will lead to an increase in the number of private schools. However, it is unlikely that the addition of these children alone can explain the magnitude of the increase in number of private schools. Based on our calculations, increases in the ability of the local student population due to influx of faculty would at most explain 1 percent of the increase in number of private schools.[34]

Supply of School Teachers: If students graduating from elite public colleges were opening up new private schools in the district and working as school teachers, it could also potentially explain our results. For instance, (20), show that private schools in Pakistan are three times more likely to emerge in villages with government girls' schools due to an increase in the supply of teachers. We do not find evidence for such an explanation. First, the first batch of students in these colleges would only graduate after 2-4 years, if an increase in the supply of teachers due to students graduating from elite public colleges was driving our results, we would not see an immediate increase in the number of private schools, and the corresponding increase in private school enrollment. The mechanism presented in (20), is inherently long-run: their paper looks at data 17 years apart. Second, it is important to note that students graduating from these highly-competitive elite public colleges are employed by technology or management firms in major Indian cities (420), making such supply-side channels less relevant in our context.

Income: $dp/dln(w) > 0$ **;** $dN_1/dln(w) > 0$

Higher education institutions may have large economic impacts on the local economy through direct increases in the supply of human capital and greater innovation, thereby increasing local incomes. These mechanisms are inherently

[34]We find an increase of 20 percentage points in the number of private schools in the year of treatment, or about 70 new schools. Each private school enrolls 200 students each, on average. Information obtained from these colleges indicate that on average these colleges have around 150 faculty members, so increases in the ability of the local student population due to influx of faculty would at most explain 1 percent of the increase in number of private schools.

long-run. Nevertheless, there exists another channel through which elite public colleges could increase family resources in the short-run: direct expenditures by faculty and students at elite public colleges. Better access to electricity, roads and water services due to elite public colleges may also increase local incomes. Such income increases may in turn increase the demand for all schooling, raising the equilibrium tuition, as well as the number of private schools.

In addition to being useful as a proxy for electrification, night lights have been used by economists as an indicator for economic activity (95; 196). It is possible that the observed impacts on night light intensity, are in fact, income effects. However, we find insufficient evidence for such an hypothesis. First, in line with our results, (75) find that a rural electrification program in India had insignificant effects on local incomes, despite causing a increase in night light intensity. Thus, electrification is not necessarily accompanied by income effects. Second, we fail to find evidence for an increase in population. It is likely that if elite public colleges increased local incomes, treatment districts would observe an increase in migration from neighboring districts. Third, we find a significant decrease in enrollment at public schools. An increase in local incomes would increase demand for all schooling. Lastly, we estimate Equation 2.3 using NSS data to examine the effects of public colleges on earnings. We fail to find evidence for an increase in wages (Figure A.34).

Aspirations: $dp/d\bar{\theta} > 0$ **;** $dN_1/d\bar{\theta} > 0$ **or Increased Perceived Returns to Education:** $dp/dr > 0$ **;** $dN_1/dr > 0$

Close proximity to elite public colleges may increase the salience of higher education, raising parental aspirations. Furthermore, the entry of elite public colleges might also alter local perceptions about returns to education due to information spillovers, and since human capital investment decisions are linked to perceived economic returns to education (e.g., (222; 260; 289)), it could increase demand for education.

If elite public colleges raised parental aspirations or altered their perceptions about returns to education, we would expect an increase in both public and private school enrollment. However, we observe a significant decrease in public school enrollment. It is unlikely that elite public colleges only affected parents' perception of returns to private schooling, or that parents who now have higher aspirations for their children perceive that private schools alone offer an easier pathway to tertiary education. We are unable to test these hypotheses directly, since we do not have an indicator for perceived returns to education or aspirations. But, insofar as an increase in perceived returns to education or aspiration translated into an increase in human capital investment, we may find an increase in children's test scores. We estimate Equation 2.3 to examine the effects of colleges on both math and reading scores in the ASER data. We fail to find evidence for an increase in test scores (Figure A.35).[35]

However, we can't rule out this explanation completely. In fact, since we observe large and immediate effects on local schooling markets, it is quite plausible that elite public colleges raised parental aspirations for children's education or increased actual or perceived returns to education because of access to public infrastructure or information diffusion.[36]

[35] As we find an increase in educational attainment, but no corresponding effect on test scores, it suggests that marginal (academically weaker) students, are being induced to stay in school longer. In many cases, interventions that improve attainment do not improve student test scores ((49; 229; 271)).

[36] For instance, (300) find that in India, IT centers increased school enrollment within few kilometers of their location, due to limited information diffusion, and that the effect is driven by changes in returns to schooling.

Access to Higher Education

Returns to education are convex, higher at the secondary and tertiary than at the primary level ((100; 349)). Correspondingly, studies have shown that parents believe that the first few years of schooling have lower returns than later years ((31; 34)). Thus, better access to higher education institutions or colleges could represent a reduction in the cost of future schooling, increasing the possibility of continuation into higher levels of schooling.

Admission into elite public colleges in India is determined by an extremely competitive nation-wide entrance exam. The Indian Institutes of Technology (IITs) has an acceptance rate of 2 percent from a pool of roughly 500,000 students. Access to elite public colleges is not a likely explanation for our results. However, if elite public colleges, like private schools, also incentivize entry of private colleges due to infrastructure upgrades, it could increase a demand for all schooling, and explain observed gains in years of schooling.

Using village level indicators for private and public college presence in the 2011 Census Village Directory, we estimate Equation 2.4 to examine effects of elite public colleges on the presence of private colleges. Private colleges are more likely to exist in villages nearest to elite public colleges (Figure A.36). The entry of private colleges could increase demand for all schooling, but given that we find a significant decrease in public school enrollment, the entry of private colleges could only explain our results if parents perceive that private schools offer an easier pathway to private colleges. Unfortunately, we can not test this hypothesis. However, it is unlikely that infrastructure upgrades increase access to private colleges but not private schools, and that private schools enter exclusively because of an increase in demand for private schooling, driven by better access to these private colleges.

Powerful Politicians

In a developing country like India, it is possible that powerful local politicians successfully lobby the federal government for both elite public colleges and public expenditure on infrastructure in their constituency or district. This would mean that changes to infrastructure and colleges are driven by powerful politicians, and not directly by elite public colleges. Although, such an explanation is compatible with supply-side factors discussed earlier, we do not find evidence for such an hypothesis. First, unless these 'powerful politicians' precisely align the timing of infrastructure upgrades with the entry of elite public colleges, we would find evidence for it in the form of pre-existing trends in our outcome variables. Second, we do not find evidence for an increase in public spending in school infrastructure: we fail to find an increase in the number of public schools. Third, out of the 42 districts that received an elite college between the period 2004-2014, almost 50 percent were represented by members from the opposition and not the ruling national coalition. Moreover, out of the districts represented by members from the ruling coalition, more than 40 percent were first time Members of Parliament (MPs). It is reasonable to assume that experienced MPs from the ruling coalition enjoy the most influence; however, since only 14 districts had MPs from the ruling coalition serving a second term or higher, political clout doesn't seems to play a significant role in the location of these elite colleges. Fourth, and most importantly, the effects of elite colleges on infrastructure are not only robust to dropping all districts governed by MPs from the ruling coalition, but marginally larger (Figure A.37).

2.8 Conclusion

In a country plagued by low literacy and school completion rates, questions are raised when public expenditure is directed towards higher rather than lower levels of education. This skepticism, however, misses the fact that higher education institutions may have 'spillover' effects on primary and secondary education markets in low-income countries like India.

In this paper, we find that elite public colleges encouraged the entry of private schools and increased private school enrollment as students switched from public to private schools. In the era of shrinking public budgets, investment in higher education facilitated the expansion of primary and secondary education with private capital. Overall, this translates into gains in educational attainment (0.3 to 0.8 years) as children stayed enrolled in school longer. In fact, our back-of-the-envelope calculations indicate that the indirect benefits of elite public colleges due to transfers to private schools,[37] and returns to extra years of primary and secondary schooling, are *at least* half the size of the direct benefits accrued through the training of undergraduate and graduate students (Appendix A.2).

Next, we find that elite public colleges crowded in focal investments in electricity, water and road services. That is, the increase in access to public infrastructure services was largest for villages closest to new elite public colleges. Importantly, we find suggestive evidence that public investment in infrastructure reduced setup costs for private schools, and the entry of private schools solved a (travel) cost constraint for marginal students, as they stayed in school longer. We explore various alternative mechanisms that might be driving the effects of

[37](281) show that although there exists little difference in output, private schools are more costs effective than public schools.

elite public colleges on primary and secondary schooling markets. While we fail to find evidence for changes in population or income as potential explanations for these effects, we can't completely rule out demand externalities such as changes in parental aspirations, or effects on actual or perceived returns to education. Indeed, as we observe large and immediate effects on local schooling markets, it is plausible that elite public colleges raised parental aspirations for children's education or increased actual or perceived returns to education due to improved information flows.

Another limitation of our analyses relates to the interpretation of these effects as spillovers from public investment in higher education. We are unable to distinguish between two nuanced interpretations: the first is that non-college public infrastructure (electricity, road, and water services) is crowded in by elite public colleges, and the second is that these investments were conceived as a "big push" policy that includes both infrastructure and higher-education components. The data appears most consistent with the former interpretation: reports in the popular press suggest that elite public colleges crowd in non-college public infrastructure. We also fail to find evidence for coordination between large public infrastructure initiatives launched in the 2000s and locations of new elite public colleges.

It is important to note that the magnitude of the effects on educational outcomes reflect district-level average treatment effects on districts where elite public colleges entered between 2004-2012. Therefore, the estimated β captures all location-level spillover effects of elite public colleges via private schools as well as the effects of roads, water, and electricity services documented in the literature. For instance, well-identified studies of the impact of school construction programs find large effects on educational attainment (140). Duflo (2001) finds that each primary school constructed per 1000 children led to an average increase of roughly 0.2 years of education in Indonesia. Distance to school is a central determinant to school choice in lower income countries (13; 84). (13) find that households are willing to pay 50% more for a reduction of 0.5 kilometers in the distance to a private school. (84) show that increasing the distance to school by 0.5 kilometers decreases the likelihood of choosing that school by roughly 5 percentage points. (243) finds that the elasticity of the probability of ever attending primary school with respect to the distance to middle school is 0.30 in Ghana. Lastly, studies have shown that access to public infrastructure services like roads, electricity, and water have large effects on education outcomes. (248) find that hydro-power plants in Brazil increased electricity access by 22 percentage points, and consequently, years of schooling by two years. (8) find that a rural road construction program in India increased middle school completion by 7%.

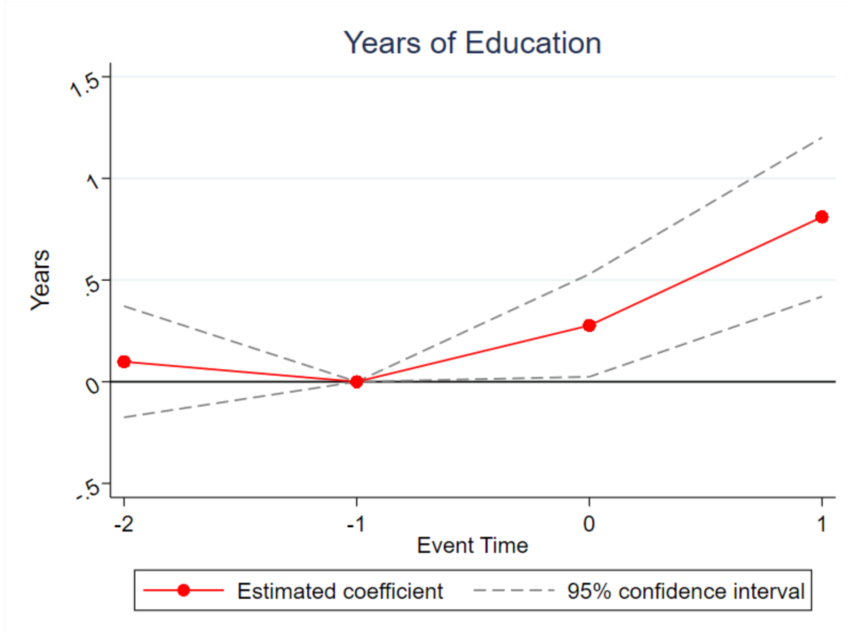
In conclusion, we would like to urge caution regarding the external validity of our findings. First, our results relate to certain *elite* public colleges in India. These colleges have been set-up since India's formative years as an independent nation and are considered extremely prestigious. Thus, new elite public colleges have been able to piggy-back off the reputation of their older counterparts and capture popular attention, even in the short run. Second, we find that elite public colleges successfully crowd-in large investments in public infrastructure services, and may be one mechanism driving our result. It is unlikely that other ('second-tier') public colleges would be able to facilitate a similar increase in access to public infrastructure. Although these concerns may constrain the broader implications of our results, elite public colleges are not unique to India.[38] More importantly, India's higher education system is the third largest in the world, next to the United States and China, and successive recent governments have pushed for a drastic and immediate increase in the number of elite public colleges in the country. In 2016-17, almost half of the budget for higher education was dedicated to elite public colleges (69). Since 2014, 25 new elite public colleges have been established across the country. To formulate an effective higher education policy in India, it is important to include any 'spillover' effects of elite public colleges in the calculation of the social returns to higher education investments.

[38] In 1998, China launched a higher education modernization process, Project 985, that intends to establish elite or 'world-class' universities across the country.

2.9 Tables and Figures

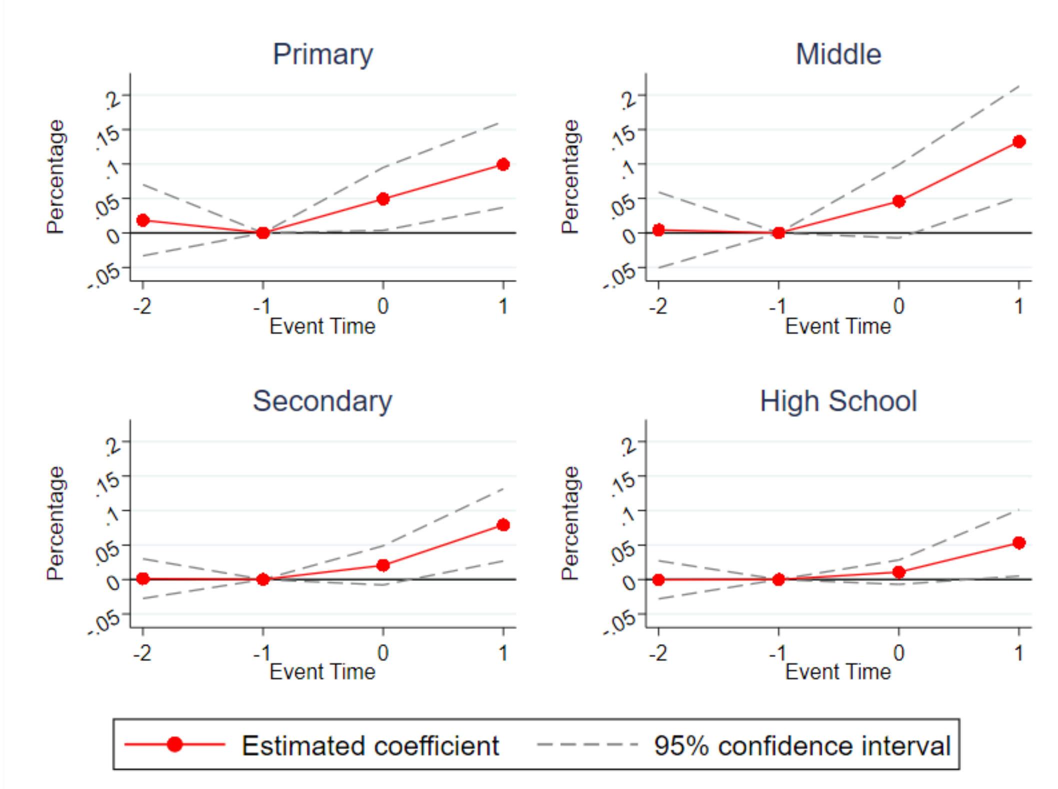
2.9.1 Figures

Figure 2.1: Impact of Elite Public Colleges on Years of Schooling (Age 6-20)



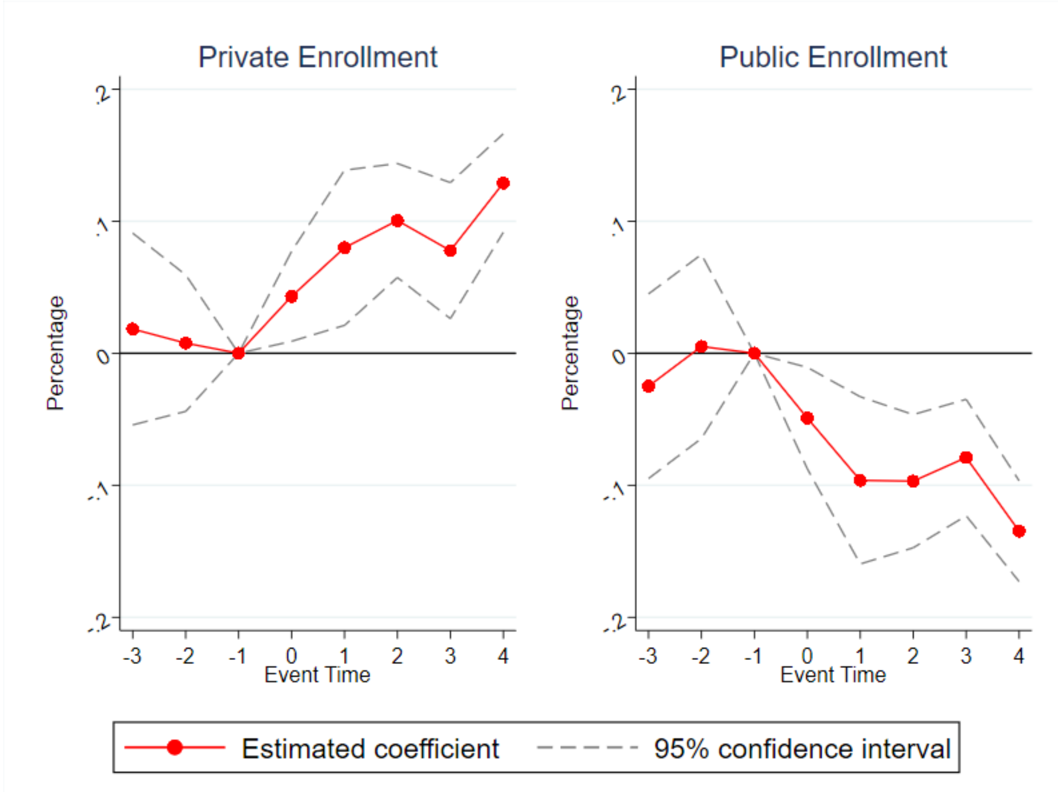
Notes: Sample includes a repeated cross-section of individuals between 6 and 20 years of age from a balanced district level panel of 25 treatment districts across 4 NSS survey rounds (2004, 2007, 2010 and 2012). The figure presents the effects of elite public colleges on years of schooling. $\tau = 0$ is the round of entry of elite public colleges. These are average treatment effects on treated districts of elite public colleges relative to the round before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2008, 2009 or 2010, the NSS surveys conduced in 2004, 2007, 2010, and 2012 are denoted as $\tau = -2$, $\tau = -1$, $\tau = 0$ and $\tau = 1$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects. 95% confidence interval is presented, standard errors are clustered at the district level. Since the NSS data is collected with time gaps, τ denotes number of survey rounds for the NSS data, where t = 2004, 2007, 2010, 2012. As a robustness check we report estimates separately by event year (Figure A.3).

Figure 2.2: Impact of Elite Public Colleges on Educational Attainment (Age 6-20)



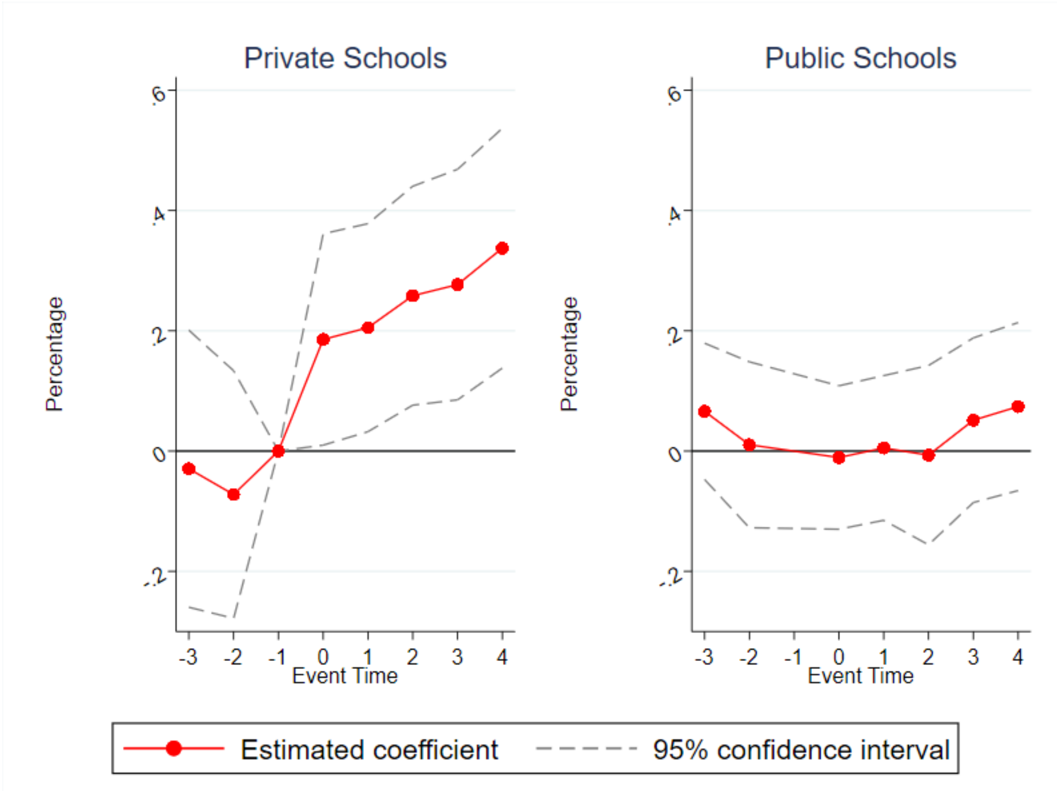
Notes: Sample includes a repeated cross-section of individuals between 6 and 20 years of age from a balanced district level panel of 25 treatment districts across 4 NSS survey rounds (2004, 2007, 2010 and 2012). The figure presents the effects of elite public colleges on educational attainment for four levels of schooling; primary school (0/1), middle school (0/1), secondary school (0/1), and high school (0/1). $\tau = 0$ is the round of entry of elite public colleges. These are average treatment effects on treated districts of elite public colleges relative to the round before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2008, 2009 or 2010, the NSS surveys conduced in 2004, 2007, 2010, and 2012 are denoted as $\tau = -2$, $\tau = -1$, $\tau = 0$ and $\tau = 1$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects. 95% confidence intervals are presented, standard errors are clustered at the district level. Since the NSS data is collected with time gaps, τ denotes number of survey rounds for the NSS data, where t = 2004, 2007, 2010, 2012. As a robustness check we report estimates separately by event year (Figure A.4).

Figure 2.3: Impact of Elite Public Colleges on Private vs. Public Enrollment (Age 5-16)



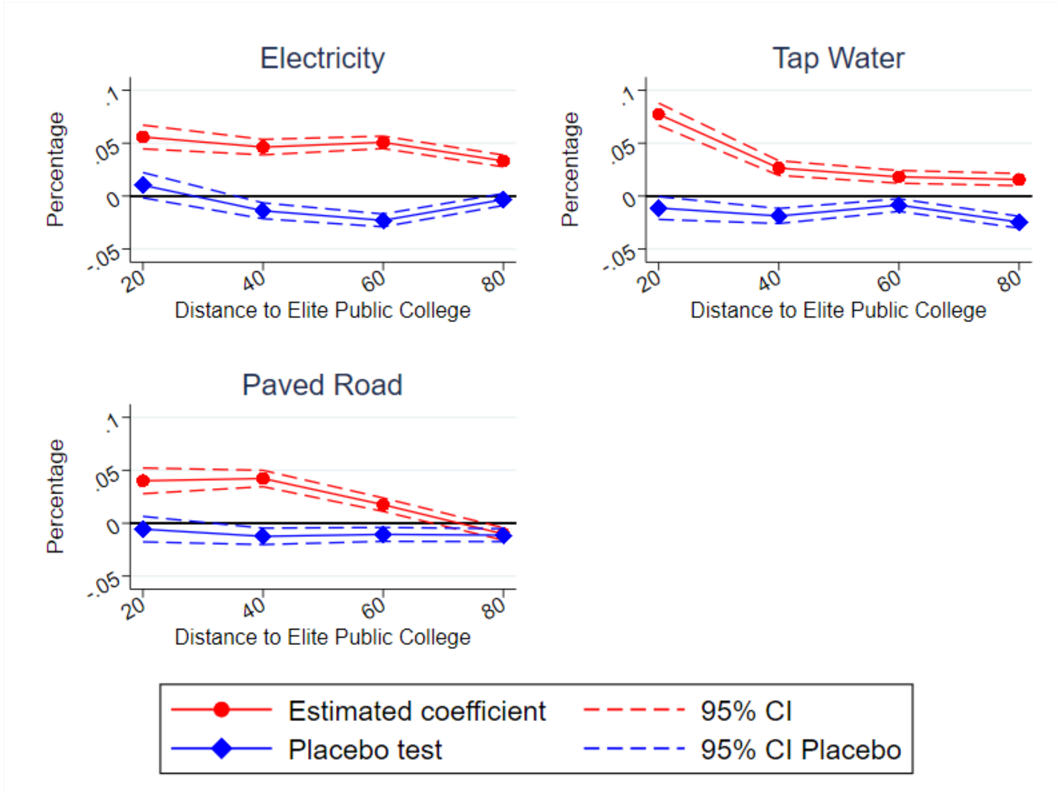
Notes: Sample includes a repeated cross-section of individuals between 5 and 16 years of age from a balanced district level panel of 14 treatment districts across 9 years of ASER data (2006-2014). The figure presents the effects of elite public colleges on private school (0/1) vs. public school (0/1) enrollment status. $\tau = 0$ is the year of entry of elite public colleges. These estimates are average treatment effects of elite public colleges relative to the year before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2009, the ASER surveys conduced in 2006, 2007, 2008, 2009, 2010, 2011, 2012, and 2013 are denoted as $\tau = -3$, $\tau = -2$, $\tau = -1$, $\tau = 0$, $\tau = 1$, $\tau = 2$, $\tau = 3$ and $\tau = 4$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects. 95% confidence intervals are presented, standard errors are clustered at the district level.

Figure 2.4: Impact of Elite Public Colleges on Private vs. Public Schools



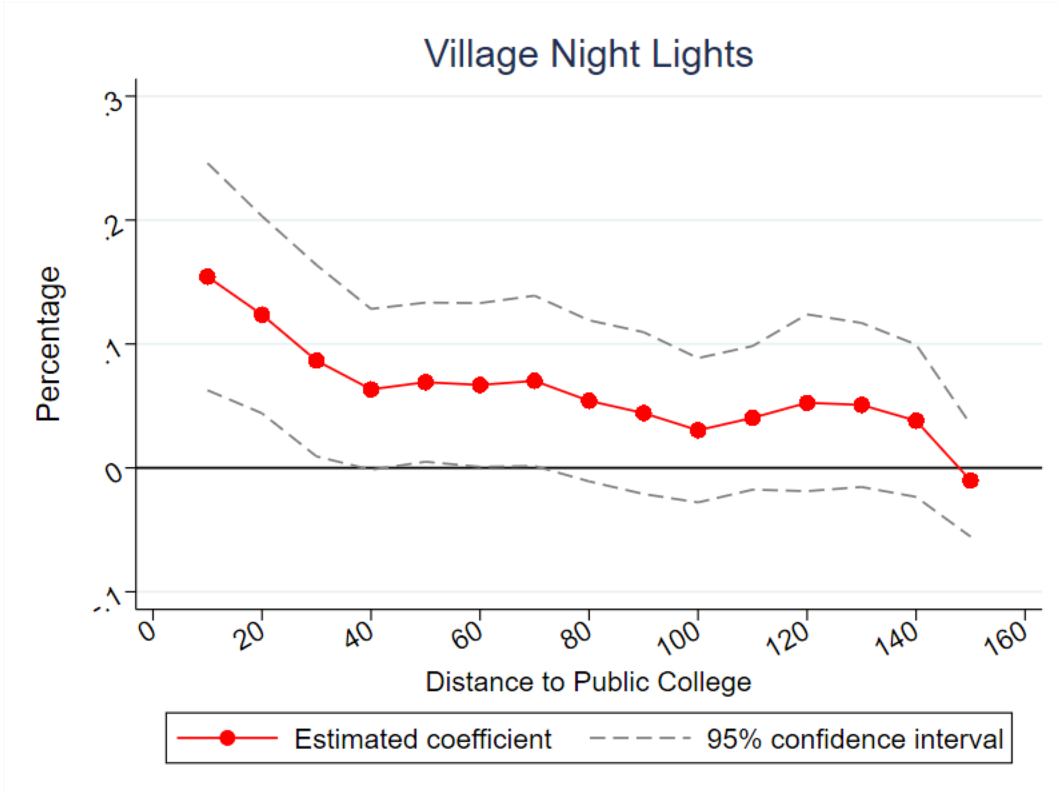
Notes: Sample includes a balanced district level panel of 23 treatment districts across 11 years of DISE data (2004-2014). The figure presents the effects of elite public colleges on number of private and public schools (natural logarithm). $\tau = 0$ is the year of entry of elite public colleges. These estimates are average treatment effects of elite public colleges relative to the year before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2007, the DISE surveys conducted in 2004, 2005, 2006, 2007, 2008, 2009, 2010, and 2011 are denoted as $\tau = -3$, $\tau = -2$, $\tau = -1$, $\tau = 0$, $\tau = 1$, $\tau = 2$, $\tau = 3$ and $\tau = 4$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects. 95% confidence intervals are presented, standard errors are clustered at the district level.

Figure 2.5: Impact of Elite Public Colleges on Access to Electricity, Tap Water and Roads



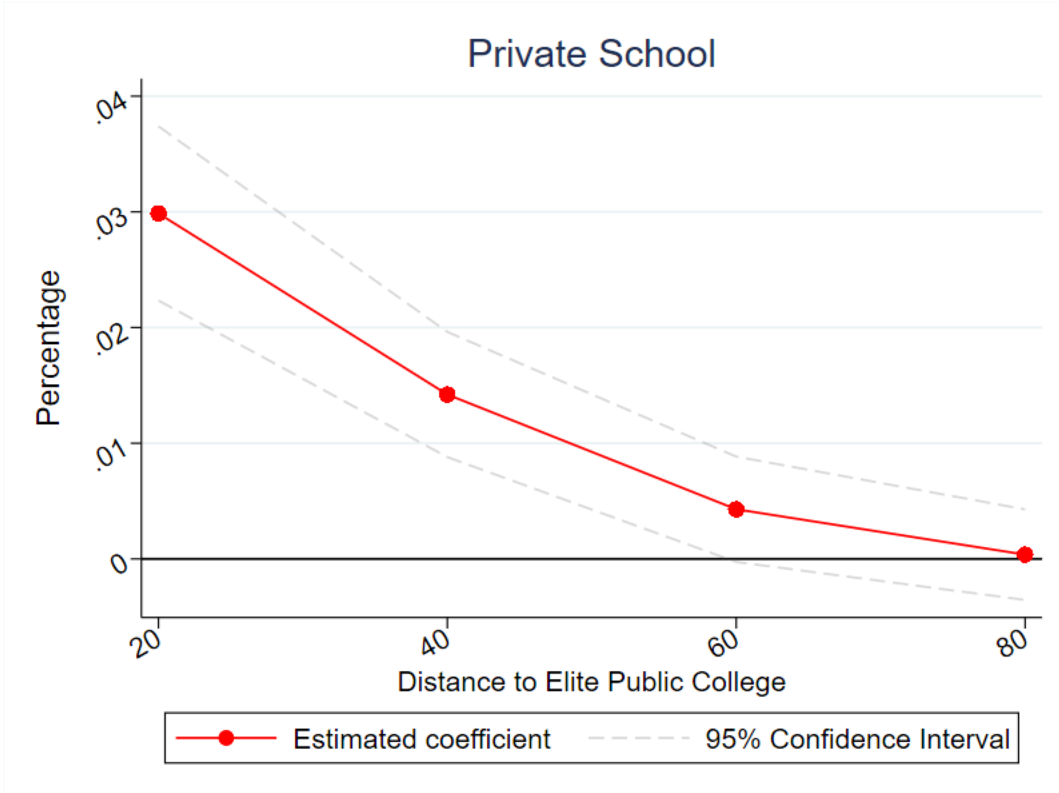
Notes: Sample includes a balanced panel of 489,576 villages across 3 Census Village Directories (1991, 2001 and 2011). The figure presents the difference-in-difference estimates of the effects of change in village-specific distance to the nearest elite public college, due to the entry of new elite public colleges between 2001 and 2011, on the change in access to village level infrastructure (electricity (0/1), tap water (0/1), and paved roads (0/1)) between 2001 and 2011. In addition, the figure also presents placebo estimates of the effects of the change in village-specific distance to the nearest elite public college, due to the entry of new elite public colleges between 2001 and 2011, on the change in access to village level infrastructure between 1991 and 2001. The regression, equation 2.4, includes district and year (round) fixed effects, as well as indicator variables that denote if the village is less than 20, 40, 60 and 80 kms away from the nearest elite public college in 2011, respectively. 95% confidence intervals are presented, standard errors are heteroskedasticity-robust.

Figure 2.6: Impact of Elite Public Colleges on Village Level Night Light Intensity



Notes: Sample includes a balanced panel of 453,921 villages across 9 years of nighttime lights data (2004-2012). The figure presents the difference-in-difference estimates of the effects of year-by-year changes in village-specific distance to the nearest elite public college, due to the entry of new elite public colleges between 2004 and 2012, on year-by-year changes in village level night lights (natural logarithm), a proxy for rural electrification. The regression, equation 2.4, includes village and year (round) fixed effects. 95% confidence intervals are presented, standard errors are clustered at the district level.

Figure 2.7: Impact of Elite Public Colleges on Private School Presence



Notes: Sample includes a balanced panel of 489,576 villages from the 2011 Census Village Directories. The figure presents the estimates of the relationship between village-specific distance to the nearest elite public college and presence of private schools (0/1) in 2011. The regression includes district fixed effects. 95% confidence intervals are presented, standard errors are heteroskedasticity-robust.

2.9.2 Tables

Table 2.1: Treatment Districts or Districts with Elite Public Colleges (2004-2014)

	Period	**# of Districts with Elite College**
	Pre-2004	40
	2004-2014	35
Balanced Panel		
Year	**# of Districts with new Elite College**	**# of new Districts with Elite College**
2004	0	0
2005	1	1
2006	2	2
2007	4	2
2008	9	6
2009	2	1
2010	13	11
2011	3	2
2012	1	1
2013	0	0
2014	0	0
Total	**35**	**26**

Notes: This table lists all elite colleges established between 2004-2014. A total of 42 elite public colleges were established in this period. Out of 42, 13 were established in 6 districts. Therefore, 35 districts received new elite colleges during this period. Out of these 35 districts, 9 districts already had an elite public college in 2003. Thus, in our analysis we only use 26 districts who that never had an elite public college and only received one between 2004-2014. Moreover, because we only use a balanced sample in our analysis, the number of districts (out of these 26) will depend on the data set used. Therefore, in NSS we use 25 treatment districts; ASER, 14; and DISE, 23.

Table 2.2: Impact of Elite Public Colleges on Distance to Private School

	(1) Distance <=1 km (0/1) Full Sample β / SE	(2) Distance <=1 km (0/1) Rural Sample β / SE
Private*2011*Public_College	0.131**	0.129*
	(0.056)	(0.067)
Mean	0.73	0.72
Observations	76659	54215
R^2	0.118	0.144

Notes: Sample includes a repeated cross-section of children between 5 and 16 years of age from a nationally representative household level panel across 2 rounds of Indian Human Development Survey (2004-05 and 2011-12). The table presents the triple difference estimates of the effects of entry of elite public colleges at the district level between 2005 and 2011 on the change in distance to private school (1 if private school is less than or equal to 1 km away from home, 0 otherwise) for children attending private school in treatment districts (or districts that received an elite public college between 2005 and 2011), $Private * 2011 * PublicCollege$. Regressions includes district fixed effects as well as an indicator variable for whether the child is attending a private school, indicator for treatment districts, indicator for survey round, and the interactions between these variables. Standard errors are in parentheses, clustered by district.

Chapter 3

Poor Sleep: Sunset Time and Human Capital Production

3.1 Introduction

Do arbitrary clock conventions help determine the geographic distribution of educational attainment levels? Proposed in the late 19th century, a system of world-wide standard time zones was intended to accumulate smaller differences in geographical longitude, so that nearby places can share a common standard for timekeeping, but still allow local time to be approximate with mean solar time. However, many countries set their own time to assert national identity, to make political connections, or to keep one time zone within their borders, even if that may take parts of their countries far out of the designated zone. India and China cover a vast east-west range, but both countries follow a standard time zone across their territorial boundaries. Clocks in large parts of the planet – e.g., France, Spain, Algeria, Senegal, South Sudan, Russia, and Argentina – are set to be ahead of their (solar) time.[1] One consequence of these discretionary clock settings are large discrepancies in when the sun sets both within and across countries.

In this paper, I show that children in locations that experience later sunsets have worse educational outcomes due to the negative relationship between sunset time and sleep, and the consequent productivity impacts of sleep deprivation. Sunset-induced sleep deficits are most pronounced among the poor, especially in periods when households face severe financial constraints. Because education is both a driver of economic growth and a means to reduce income inequality (41), these results imply sunset time associated with geographic location may contribute to persistent poverty and worsening inequality.

As the sun sets and the sky grows darker, the human brain releases melatonin, a hormone that facilitates sleep (325). Yet social norms or uniform policy choices at the federal or state level – for example, start times for school and work – may dictate wake-up times that do not co-vary with sunset time (185). As a result, children may sleep less in locations exposed to later sunsets. If sleep is productivity-enhancing, later sunset may directly, adversely, affect children's learning.

However, the consequent effect of later sunsets on educational attainment is ambiguous; how children trade-off sleep with other time uses may have multiplicative or compensatory effects on education production. If sleep makes study effort more productive, later sunset may not only reduce sleep but also

[1]For instance, Spain switched clocks ahead one hour to be in sync with Germany in 1940, even though Spain is geographically in line with Britain, not Germany.

make studying less effective, decreasing study time. Conversely, later sunset (more daylight after school) might make it easier for children to self-study in the evening, especially in lower income countries where electricity access is intermittent. Moreover, child labor is common in lower income countries. Therefore, any complementarities between sleep and study effort may also depend on the marginal increase in children's labor productivity with respect to sleep. As an additional channel, later sunset may similarly affect adults' sleep, and consequently household earnings and investment in children's education.

The timing of natural light is determined by time zones and is therefore predictable across locations and seasons. If sleep is important for productivity, households may adjust their sleep schedules in response to later sunset, or simply get on a consistent sleep schedule regardless of sunset time, minimizing the resulting human capital impacts. Yet, financial or behavioral considerations may impede adjusted or consistent sleep. More importantly, poverty may exacerbate these considerations.[2] Therefore, if the non-poor are better able to adjust their sleep schedules when the sun sets later, later sunsets may contribute to a sleep disparity in the population.

In the first part of the paper, I use the 1998-99 Indian Time Use Survey (ITUS) to evaluate the effect of later sunset on children's time use. ITUS provides 24-hour time use data, collected with less than a 24-hour recall lapse, allowing me

[2]While urban environments, inaccurate self-perceptions of fatigue (411), or time inconsistency (67) may constrain adjustment regardless of socioeconomic status, sleep environments among low-income households in particular are associated with noise, heat, mosquitoes, overcrowding, and overall uncomfortable physical conditions (180; 310). The poor, however, may lack the financial resources to invest in sleep-inducing goods (e.g., window shades, separate rooms, indoor beds, food) and adjust their sleep schedules on later sunset days. In addition, poverty may have particular psychological consequences (e.g., stress, negative affective states, increase in cognitive load) that can affect decision-making (191; 259; 342). Thus, cognitive considerations associated with poverty may make it harder to assess one's own sleep-productivity relationship and optimize sleep schedules when the sun sets later.

to assign each observation a district-date sunset time. My baseline econometric specification exploits seasonal variation in *daily sunset time* at the district level after controlling for fixed district-specific characteristics as well as seasonal confounders common across all districts in the sample.

I show that an hour (approximately two standard deviations) delay in sunset time reduces children's sleep by roughly 30 minutes: when the sun sets later, children go to bed later; by contrast, wake-up times are not regulated by solar cues. Sleep-deprived children decrease productive effort: later sunset reduces students' time spent on homework or studying, as well as child laborers' time spent on formal and informal work, while increasing time spent on sedentary and compensatory leisure for all children. This result is consistent with a model where sleep is productivity-enhancing and increases the marginal returns of study effort for students and work effort for child laborers.

The second part of the paper examines the consequent *'lifetime'* or *long-run* impacts of later sunset on stock indicators of children's academic outcomes. I use nationally-representative data from the 2015 India Demographic and Health Survey (DHS) to estimate how children's education outcomes co-vary with *annual average sunset time* across eastern and western locations within a district.[3] I find that an hour (approximately two standard deviations) delay in annual average sunset time reduces years of education by 0.8 years. School-age children in geographic locations that experience later sunsets are less likely to complete primary and middle school, are less likely to be enrolled in school, and have lower test scores. In addition, using an individual level longitudinal panel, wherein the same child is administered comprehensive math tests at different dates ev-

[3]A one hour difference in annual average sunset time between two locations indicates that on average the sun sets an hour later *everyday* in one location compared to the other location.

ery survey round, I leverage seasonal variation in sunset time at the district-test-date level across survey rounds to document the deleterious short-run effects of sunset-induced sleep deficits on children's test scores.

To argue that these results are generalizable, I use data from China and Indonesia. Unlike ITUS, the 2004-2009 China Health and Nutrition Survey collects data on children's time use for a 'typical' day of the year, and not for a particular date. I use cross-sectional variation in annual average sunset time across districts within a state. In line with my India estimates, an hour delay in annual average sunset time reduces children's sleep by roughly 30 minutes. To corroborate the effects of later sunset on children's academic outcomes, I use the 2003 Indonesia DHS, employing a sharp regression discontinuity design that exploits time zone boundaries in Kalimantan, Indonesia. I find that an hour delay in annual average sunset time reduces years of schooling by 0.7 years, quite similar to my India estimate.

The third part of the paper shows that parental education investment may be an additional channel through which later sunset affects human capital production. Using ITUS, I find that an hour delay in sunset time reduces adults' sleep by 30 minutes. Later sunset also reduces adults' earnings in India.

In the fourth part of the paper, I investigate if poverty helps explain why families fail to adjust their sleep schedules when the sun sets later. Initially, I examine heterogeneous impacts of later sunset on sleep by correlates of poverty (e.g., education, average monthly expenditure) in India. The negative effect of later sunset on sleep is at least 25% larger among low socioeconomic status (SES) households compared to high SES households. To evaluate whether this heterogeneity truly reflects the influence of poverty, I restrict the ITUS sample to crop cultivator households, and exploit quasi-experimental variation in income around the harvest period, comparing the effect of later sunset on sleep in the month before harvest, when crop cultivator households are poorer and typically liquidity constrained, with the month after harvest, when richer and more financially liquid. Because harvest calendars vary across seasons and locations, I also control for all fixed differences between time periods and districts. Indeed, sunset-induced sleep deficits are significantly larger before harvest compared to after harvest. I show this effect is not driven by possible changes in work effort on later sunset days. Overall, financial and psychological considerations associated with poverty help explains 25-100% of the effect of later sunset on sleep.[4]

The rest of the paper is organized as follows. In Section 3.2 we provide a brief literature review. Section 3.3 provides a conceptual framework to understand how children trade-off sleep with other time uses. Section 3.4 describes the data. Section 3.5 investigates the effects of later sunset on children's time use, while Section 3.6 examines the consequent effects on children's education outcomes. Section 3.7 evaluates the effects of later sunset on adults' time use and wages. Section 3.8 examines poverty as one potential explanation for why individuals fail to adjust their sleep schedules when the sun sets later. Section 3.9 provides a back-of-the-envelope estimate for the human capital costs associated with existing policy regulating time zone boundaries in India, while Section 3.10 concludes.

[4]Like previous studies (89; 259; 367), this result speaks to the effects of sharp, anticipated but short-lived variations in financial resources around the 'payday' (harvest) period. It is this particular impoverishment that I allude to when I refer to "poverty." Although the heterogeneous effects on sleep by socioeconomic status suggest similar effects for a permanent shift in permanent income, the interpretation of these estimates may be confounded by omitted variables that are correlated with socioeconomic status.

3.2 Contributions to the Literature

Recent evidence suggests that both natural environment and institutions are important for economic development: Fixed features of the natural environment (e.g., latitude, distance from coast, elevation) have considerable influence on contemporaneous economic outcomes ((17; 59; 270; 295; 297)); and, political and economic institutions are important determinants of long-run economic growth ((4; 292; 293; 324)). However, these relationships are often studied in isolation. I provide evidence that arbitrary human institutions may interact with fixed features of the natural environment to produce bad economic outcomes.

I contribute to a new literature that examines how arbitrary clock settings – by generating differences in the timing of natural light – affect economic outcomes.[5] Within this literature, a small set of papers evaluate the implications of the relationship between sunset time and sleep. (173) observe associated impacts of later sunset on adult wages in the US, while (175) and (174) investigate consequent effects on adult health outcomes in the US and China, respectively. I provide the first evidence that differences in when the sun sets across locations – by generating long-term differences in sleep – help determine the geographic

[5] A few papers exploit variation in the timing of natural light due to daylight savings time (DST) in the US to investigate short-run effects on a number of economic outcomes: (136) (crime), (421) (outdoor leisure), (224) (health) and (363) (automobile accidents). Two studies also examine the relationship between daylight savings time transitions and test scores but find contrasting results: using the variation in DST regimes among counties in Indiana, (166) show that SAT scores are significantly worse in counties that advance and set back their clocks each year as compared to counties sticking to standard time permanently; (197) use international assessment data from six European countries and fail to find evidence that the transition into daylight saving time affects elementary students' performance in low-stakes tests in the week after the time change. In any case, if one were to compare short-run effects of sleep deprivation from daylight savings time onset, to the long-run effects of sleep deprivation at issue in this paper, two differences have offsetting effects. First, effects of sleep deprivation on education production could accumulate; the DST transition may only affect sleep for a few days, while later sunset affects sleep every day. Second, there may be adaptation to a permanent shift in sunset time.

distribution of educational attainment levels. A growing body of work suggests that education offers a wide-range of benefits that extend beyond increases in labor market productivity: improvements in education can lower crime, improve health, and increase voting and democratic participation (250). Therefore, policies that promote children's sleep may also improve later-life well-being in locations exposed to later sunsets.

This paper also relates to several recent studies that examine the short-term consequences of later school start times on students' academic performance in the US (86; 147; 195; 198; 414). (198) studies a policy change in public school start times in Minneapolis but fails to find evidence that ringing the school bell later increases student performance on a high school achievement test. (195) show that moving school start times one hour later relative to sunrise increases test scores for adolescents in Florida. (86) exploit random assignment of school schedules at the United States Air Force Academy and find that later school start times improve test scores among freshmen cadets. These effects (or lack thereof) are mediated through changes in children's time use, although the above-mentioned papers do not observe children's sleep or consequent trade-offs with other uses of time. My results provide the first evidence on the long-run importance of child sleep for learning outcomes.

Furthermore, I estimate how children trade off sunset-induced sleep deficits with time allocated to studying or homework (study effort) and formal or informal work (work effort), in a context where child labor is prevalent. (54) model sleep as a choice variable that affects productivity, although they did not focus on this relationship in their empirical analysis. (173) investigate how sleep deprivation induces trade-offs between sleep and productive effort. However, their findings relate only to adults. Unlike the American Time Use Survey, ITUS collects time use data for children. My results suggest that sleep is productivity-enhancing, increasing the marginal returns of self-investment in study effort for students, and the marginal product of work effort for child laborers. Because sleep is the largest use of non-market time, these results also relate to seminal papers of (276) and (45), as well as recent work by (10), that emphasize that labor supply is influenced by how time is allocated outside of market work.

Lastly, this study contributes to a large literature in the broader social sciences that explores the relationship between poverty and counterproductive behavior. The poor use less preventive health care (227), fail to adhere to drug regimens (135), are tardier and less likely to keep appointments (226; 286), are less attentive parents (266), and worse managers of their finances (37; 57; 146). There is also some descriptive evidence from the US that suggests sleep deprivation is higher among the poor (180; 310). I provide the first evidence for a plausibly causal relationship between poverty and sleep.[6]

3.3 A Conceptual Framework of Children's Time Use

Sleep deprivation impairs learning and cognition (47; 230; 246; 247; 318; 337; 351; 413), and the impacts increase with the cumulative extent of sleep deprivation

[6]Because families get less sleep on days the sun sets later in periods when liquidity constraints bind tightly compared to later sunset days in periods when households are more financial liquid, this paper also contributes to studies that show liquidity constraints impede 'adoption' of welfare improving technologies (e.g., piped water, migration, cookstove, bednets) in developing countries (44; 68; 131; 277; 378).

(42; 411). Thus, if later sunset reduces the time allocated to sleep, children that observe later sunsets may have non-trivial sleep deficits with real human capital impacts.

However, the consequent impact of later sunset on schooling outcomes is ambiguous; how children trade-off sleep with other time uses may have multiplicative or compensatory effects on education production. If sleep were not productive, then it would be a substitute for other time uses, including productive effort. For example, later sunset (more daylight after school) might make it easier for children to self-study, especially in lower income countries where electricity access is intermittent. On the other hand, if sleep is productivity-enhancing and increases the marginal returns of an extra hour of productive effort, sleep deficient children may decrease self-investment in study effort.[7][8] Moreover, in a context where child labor is pervasive, complementarities between sleep and study effort may also depend on the marginal increase in wages with respect to sleep.[9]

To formally examine how children trade-off sunset-induced reduction in sleep with other time uses, I extend the productive sleep model from (173) – an extension of the time use model of (182) – to children. The child's problem is to maximize a utility function $u(x, L)$ where x are consumables, and L is leisure time. u is weakly increasing in each argument and is quasi-concave. I assume that parents induce children's investment in schooling through parental trans-

[7] Several studies document a positive relationship between children's self-investment in study effort and learning outcomes (12; 62; 137; 149; 372; 373).

[8] Instead, children may allocate more time to indoor leisure. Multiple studies have shown that sleep deprivation increases daytime sleepiness and sedentary leisure activities (87; 88; 153; 217; 256; 301; 338). The effects of leisure, specifically, exposure to media, on children's cognitive outcomes has been mixed (157; 168; 258).

[9] Even today India has roughly 9 million child laborers (90). Also, the average Indian child allocates considerably more time to labor activities than the average child in an advanced economy like the UK (Figure B.1).

fers (46).[10] Thus, the child's consumables depend on earnings through own labor, x_O, earned by working for parents, and reward, r, set by parents for educational achievement.

Work time is denoted as N, thus the child can gain output, $x_O = NW(S)$, where $W(S)$, is wage received from parents, and is a function of children's sleep, S. Price is normalized to 1. Similarly, the child can also gain goods, $x_H = rh(H, S)$, where reward, r, can be thought of as a parent's present discounted value of the returns to child's achievement in the current period, and $h(H, S)$ is the education production function, with inputs H, denoting time spent on schooling, including self investment in study effort. Thus, total consumables are given by $x = x_O + x_H$. I assume that the parent has full information and can fully commit to this contract. I model sleep as productivity-enhancing, more sleep will, *ceteris paribus*, increase labor productivity ($\frac{\partial W(S)}{\partial S} > 0$) and educational achievement ($\frac{\partial h(H,S)}{\partial S} > 0$). However, the total effect of sleep on earnings and achievement, and hence parental transfers, also depends on how children trade-off sleep with work ($\frac{\partial N}{\partial S}$), study time ($\frac{\partial H}{\partial S}$), and leisure time ($\frac{\partial L}{\partial S}$).

Putting all time uses together, the total time constraint is $T = L + H + N + S$. Substituting the time budget into the goods budget, the combined budget constraint is

$$x_H = rh(T - L - S - N, S) \tag{3.1}$$

and the optimization problem is

$$\max_{L,N,S} \tag{3.2}$$

$$u(NW(S) + x_H, L) + \lambda_1(rh(T - L - S - N, S) - x_H) + \lambda_2 N + \lambda_3 S$$

[10]Alternatively, I can assume that children's allocation of time is driven by their own preferences. Households behave like an internal market in which children select their optimal time allocation bundle, and are rewarded accordingly (233).

Consider a child who is a student, but also works at home or in the market. Also, assume sleep is positive, so $N > 0$, $S > 0$, and $\lambda_2 = \lambda_3 = 0$, by complementary slackness. Further, $h_1' > 0$, $h_2' > 0$, $h_{11}'' < 0$, and $h_{22}'' < 0$. First order conditions can be written as

$$\frac{u_2'}{u_1'} = rh_1' \tag{3.3}$$

$$W(S) = rh_1' \tag{3.4}$$

$$NW'(S) + rh_2' = rh_1' \tag{3.5}$$

Taking the total derivative of Equation 3.4, I get

$$\frac{dH}{dS} = \frac{W'(S) - rh_{12}''(H^*, S^*)}{h_{11}''(H^*, S^*)} \tag{3.6}$$

Thus, $\frac{dH}{dS} > 0$ if $W'(S) < rh_{12}''(H^*, S^*)$; sleep will induce study effort if marginal increase in school productivity with respect to sleep is larger than the marginal increase in wages (labor productivity) with respect to sleep. However, if the opposite condition holds, $W'(S) > rh_{12}''(H^*, S^*)$, then increase in sleep will reduce self-investment in study effort $\frac{dH}{dS} < 0$. Assume that for any student i or child whose primary activity is education, sleep will be more achievement-enhancing than work-productivity enhancing ($W'(S) < rh_{12}''(H^*, S^*)$), while for any child laborer j, sleep will be more work productivity-enhancing than achievement enhancing. That is, child i or j will have no incentive to switch his or her primary activity due to the productivity impacts of sleep.

Taking the total derivative of Equation 3.5,

$$\frac{dN}{dS} = \frac{[rh''_{11}(H^*,S^*) - rh''_{21}(H^*,S^*)]\frac{dH}{dS} + rh''_{12}(H^*,S^*) - rh''_{22}(H^*,S^*) - NW''(S)}{W'(S)} \tag{3.7}$$

Assume $W''(S) \leq 0$, and sleep is productive: $h''_{21}(H^*,S^*) > 0$ and $W'(S) > 0$, if $\frac{dH}{dS} < 0$, then $\frac{dN}{dS} > 0$.[11] So, sleep can either be work productivity enhancing or achievement-enhancing.[12]

To summarize, the model predicts that sleep increases study effort if sleep is more achievement-enhancing than work-productivity enhancing. The increase in achievement will be large enough to lead to an overall increase in the amount of study time. But if sleep is more work-productivity enhancing than achievement-enhancing, then sleep will increase work time.

If, however, sleep is not productivity-enhancing, reducing sleep will cause a pure income effect for the child, and depending on the utility function, study, work and leisure time may increase. Sleep will be a substitute for all other time uses.

3.4 Data

I use detailed time use and education data from India to analyze the negative relationship between sunset time, sleep, and education production. I corroborate key results using time use data from China and education data from Indonesia. The features of the core data sets that are most relevant for my analysis are described below. Appendix B.1 describes supplementary data; it also includes a

[11]Medical studies often find a nonlinear relationship between sleep and health that suggests $W''(S) < 0$ (82). (411) find that cognition declines linearly with sleep deprivation.

[12]An increase in duration of productive sleep induces an increase in 'wages', so income and substitution effects make the sign of the net effect on leisure time ambiguous.

short discussion on daily sunset time and annual average sunset time, generated using the solar mechanics algorithms from (267).

3.4.1 India Time Use Survey (ITUS)

ITUS is the first time use survey of its size and coverage amongst developing countries. Over 18,000 households were surveyed in 52 districts across 6 states between July, 1998 and June, 1999. States were selected to give geographical representation to each region of the country. Within each state, households were randomly selected based on a sampling procedure designed to ensure a representative sample at the state level. The survey was spread over one year to account for seasonal variation in activity patterns.

Time use data were collected for all household members over five years of age. Thus, ITUS collects time use data for children, which is rare amongst such surveys.[13] For each household, time use data were collected for three types of days: normal (usually weekdays), weekly variant (usually Sundays), and abnormal (festivals or holidays). Initially, an investigator collected information for these three types of days within the week from different members of the selected households. Then, the investigator revisited households accordingly and interviewed individuals about their time allocation decisions for those particular days. Using the interview date and district identifiers, I determine sunset time for each individual corresponding to the date for which the time use data

[13]For instance, the American Time Use Survey only collects data for individuals over fourteen years of age.

were collected.[14][15]

To examine the effects of later sunset on children's time use, I restrict the sample to school-age children less than 17 years of age. 55% of children in the sample are male, and 70% reside in rural areas. Importantly, the primary activity is schooling for only 8 out of 10 children; 19% of the sample of school-age children primarily engages in some form of child labor. On average, 6 out of 7 days in a week are normal days, while only 1 day is a weekly variant suggesting 6-day work/study weeks. Correspondingly, time use data for only 4% of the normal day sample were collected for a Sunday, while time use data for 66% of the weekly variant sample were collected on a Sunday.[16] Thus, I will refer to the normal day sample as the 'weekday' sample, while the weekly variant sample as the 'weekend' sample.

In the survey, daily activities were classified in roughly 150 activities across 9 broad categories: 1) primary production, 2) secondary production, 3) trade, business and services, 4) household maintenance, management and shopping for own households, 5) care for children, sick and elderly, 6) community services

[14]For instance, if the normal date for an individual was a Monday, the investigator visited the individual on Tuesday of the same week to collect time use data for that prior Monday. That is, interviews were conducted such that time use data could be collected with less than a 24-hour recall lapse. See (303), for a detailed overview of the sampling strategy and data collection methods. Self-reported time use data may be prone to measurement error. For example, self-reported sleep tends to overestimate objective measures of sleep duration (242). However, it is unlikely that any measurement error is systematically correlated with the sunset time. In addition, it is reassuring that I obtain similar results from time use surveys in both India and China.

[15]Table B.1 presents the monthly distribution of interview dates by state. Figure B.2 maps of districts in ITUS. Figure B.3(a) shows variation in daily sunset time for all 52 ITUS districts, while Figure B.3(b) shows variation in daily sunset time for dates for which time use data was collected in the sampled districts. The amplitude of the wave is determined by the latitude of the location, and the vertical translations are due to longitude or east-west variation in sunset time across India. There is no reason to believe that the date of time use data would be correlated with sunset times. However, I examine this assumption explicitly, and fail to find evidence for any such relationship (Table B.2).

[16]Table B.3 presents summary statistics for both the normal day and the weekly variant sample.

and help to other households, 7) learning, 8) social and cultural activities, mass media etc., and 9) personal care and self-maintenance. Appendix B.1 includes a complete list of all activities as classified in ITUS. I further grouped these categories into five brackets: sleep, study, school, leisure, and work. 'Work' includes categories 1 to 6,[17] while 'leisure' all items from categories 8 and 9 except sleep. Category 9 includes 'sleep and related activities', or all sleep during the course of a 24-hour period. I include nighttime sleep or any sleep that starts and ends between 6 pm and 12 pm in the variable 'sleep' and not 'leisure'. Naps, however, are included in 'leisure'.[18] 'Study' includes time spent on homework, tuition, and course review, while 'school' includes time spent in an educational institution like a school or university.

On weekdays, school-age children spent on average 9 hours/day on sleep, 7.5 hours/day on leisure activities, and almost 4 hours/day in school. School-age children spent over 2 hours/day on average on work, but less than 1.5 hours/day on educational activities outside of school. On weekends, children don't have school, so they allocate more time to sleeping at night, studying, and on leisure activities.

School-age children tend to go to bed after 7 pm, and wake up by 7 am on weekdays. They also tend to self-study (e.g., homework) early in the morning, before school, and then after school, later in the afternoon. Time allocation to

[17]Both market work and home production are included in 'work' for convenience as female child laborers tend to work at home while male child laborers typically perform outdoor tasks.

[18]Like (173), I exclude naps or daytime sleep from 'sleep'. I define daytime sleep or naps as sleep that starts and ends during afternoon hours (between 12 pm and 6 pm). I include naps in 'leisure', but napping may be an adaptation to later sunset, undertaken for the compensatory effects rather than because it is pleasurable. Thus, I examine the nighttime to daytime sleep trade-offs. Indeed, I show that later sunset increases nap time by roughly 15 minutes. However, as discussed in Appendix B.2, naps may momentarily increase basic concentration under conditions of sleep deprivation, but cannot salvage more complex functions of the brain, including learning.

recreational activities is spread throughout the day. Work schedules are similar to school schedules but not as intensive, on average.[19]

Compared to developed countries, children in India spend less time on sleep and leisure, but more time studying outside of school, and on work-related activities. Given such prevalence of child labor, I also examine time allocations by primary activity: 'student' or 'worker', which is indicated in ITUS. Students or children attending school spent less than 1 hour/day on work, while spending 5 hours/day in school and 2 hours/day studying outside of school.[20] However, child workers allocated almost 6 hours/day on average to work. Finally, children engaged in child labor allocated more time to leisure than those who were primarily students.[21]

[19]Figure B.4 presents the average time spent by children on sleep, study, school, leisure and work, respectively. Figure B.5 describes sleep patterns on a weekday among children. I also directly examine the average bed- and wake-up times for children for both weekdays and weekends in Figure B.6. I find no differences in bedtimes, and only a small increase in wake-up times during weekends. Figure B.7 examines time allocation patterns for other activities within a weekday. In Table B.4 I show the average number of individuals who sleep above certain thresholds of sleep (7, 8, 9, 10 or 11 hours) by age group; 70% (44%) children between 6 and 13 years (14 and 16 years) of age sleep at least 9 hours. Recently, a NSF assembled multidisciplinary expert panel recommended that children between 6 and 13 years of age sleep 9 to 11 hours while those between 14 and 16 years of age were recommended to sleep at 8 to 10 hours (199).

[20]Figures B.8 and B.9 describe how students and child laborers spend their time on weekdays and weekends.

[21]Figures B.10 and B.11 present correlations between sunset time and children's time use using the raw data. Within each district, I disaggregate children into two groups: children interviewed when seasonal sunsets were below 25th percentile (early sunset), and those interviewed when seasonal sunsets were above 75th percentile (late sunset). Compared to days with early sunset, on late sunset days children start sleep later, but wake-up times remained unaffected. Furthermore, children spend less time studying, and more time on leisure. Importantly, while effects on sleep patterns are similar for both students and workers (Figure B.12), late sunset reduces study time for students, but work time for workers, with comparatively modest effects on work time for students and study time for workers (Figure B.13).

3.4.2 Demographic and Health Surveys (DHS)

The DHS are nationally-representative demographic surveys collected for USAID in collaboration with governments of the countries where the surveys are fielded. These data represent the widely-accepted gold standard for demographic and health data in the developing world. The DHS collects basic education data for every member in the sample household. In addition, DHS data also contain a variety of household-level survey data related to assets and household physical infrastructure. Importantly, DHS data includes geolocation information allowing me to generate annual average sunset time at the primary sampling unit (PSU) level. PSUs correspond to a village in rural areas and city blocks in urban areas. Because my core time use data are from India, I primarily draw on the 2015 India DHS. I use the 2003 Indonesia DHS to argue that my results are generalizable and because it allows me to leverage a different source of variation in sunset time.

Using the 2015 Indian DHS, I exploit cross-sectional variation in annual average sunset time across eastern and western PSUs within small administrative divisions. Next, I use the 2003 Indonesian DHS. Kalimantan is the Indonesian portion of the island of Borneo with two time zones: UTC+7 and UTC+8. I leverage a sharp discontinuity in annual average sunset time at the time zone boundary to corroborate the effects of later annual average sunset on children's academic outcomes.[22]

I restrict the sample to household members between 6 and 16 years of age across both countries.[23] In the 2015 Indian DHS, the average school-age child

[22]Although Indonesia has multiple islands on different time zones, Kalimantan is the only contiguous Indonesian island with an internal time zone border.

[23]Table B.5 presents summary statistics for outcomes of interest. In India (Indonesia), the

has roughly 4.5 years of schooling; 48% have completed primary school and 21% completed middle school. In the 2003 Indonesian DHS, the average school-age child has completed roughly 4 years of schooling. 34% have completed primary school and 10% have completed middle school.

3.5 Effects of Later Sunset on Children's Time Use

In this section, I use detailed time use data from India to examine how daily sunset time co-vary with children's time use, in particular, sleep and study effort, at the district level. To corroborate these effects, I use time use data from China, exploiting cross-sectional variation in annual average sunset time.

3.5.1 Empirical Model

To formally examine the relationship between sunset time and children's time allocation, I use ITUS and estimate the following econometric model:

$$y_{idwt} = \beta Sunset_{dwt} + \mu_w + \mu_d + \epsilon_{idwt} \tag{3.8}$$

To identify the average effect of an hour increase in sunset time (β), time allocated to sleep, study, leisure or work (y_{idwt}), by child i, in district d, on date t,

levels of the education system are as follows: primary school ranges from grade 1 (1) to grade 5 (6) and middle school ranges from grade 6 (7) to grade 8 (9). Figure B.14 presents the location of PSUs across India, while Figure B.15 shows the distribution of annual average sunset time across these PSUs.

during week-of-year w, is regressed on sunset time observed in district d on date t ($Sunset_{dwt}$). μ_w are week-of-year fixed effects, and μ_d are district fixed effects. Thus, I control for attributes that vary by week-of-year, that is seasonal trends common across districts in the sample (e.g., national festivals), as well as fixed district-specific characteristics (e.g., electricity access), that affect children's time allocation decisions. My parameter of interest that relates sunset to time allocation are identified from intra-annual or seasonal variation in daily sunset time at the district level after controlling for seasonal variation common across all districts in the sample. Put another way, the estimates are identified from the comparison of districts that observed a late sunset day with ones that observed an early sunset day within the same week-of-year, after absorbing fixed district-specific unobservables.[24] I cluster standard errors by district-week for three reasons: to allow for arbitrary spatial correlation across children within a district, to allow for autocorrelation in time allocation within a week, and to account for the fact that the same sunset time can be assigned to multiple children. I demonstrate below that results are insensitive to numerous robustness checks, supporting the validity of my baseline model.

3.5.2 Results

First, I investigate the effect of late sunset on children's bedtime and wake-up time. Consistent with the above-mentioned medical literature on human circadian rhythm, later sunset delays bedtimes. A one hour (approximately two

[24]The identification of daily sunset time effects relies on variation in the timing of time use dates. The ITUS was not designed to be representative at the daily level, so I demonstrate balance by examining the relationship between sunset time and socioeconomic factors at the individual level (e.g., wealth, sex, age) as well as interview date characteristics (e.g., day-of-week). I fail to find evidence for a statistically significant relationship between sunset time and individual or household-level observables (Tables B.9 - B.11).

standard deviation) delay in sunset delays bedtime by an estimated 0.36 hours (Table 3.1). Children fail to compensate by waking up later as wake-up times do not co-vary with sunset times.

Next, I evaluate the effects of sunset time on sleep, study, leisure and work. In line with the previous result, Table 3.2 shows that a one hour delay in sunset reduces sleep by 0.47 hours or roughly 30 minutes. Furthermore, later sunset significantly reduces self-investment in study effort, but increases time spent on leisure. An hour delay in sunset reduces study time by 0.67 hours, increasing leisure by 1.65 hours. Indeed, sleep complements study effort and substitutes with leisure.[25][26]

These aggregate results mask substantial heterogeneity by children's primary activity. While effects on sleep are qualitatively similar for both students and child workers,[27] late sunset reduces study time for students and work time for workers, with comparatively modest effects on work time for students and on study time for workers (Table 3.3).[28] These effects suggest that sleep increases the marginal gains of an extra hour of study effort for students with comparatively modest marginal gains for labor productivity. Conversely, for child laborers the increase in marginal product of labor from an extra hour of

[25] A large fraction of observations have values of zero for the time spent on study and work effort. Thus, Table B.12 also presents the Tobit estimates and find that these results are in line with the OLS estimates, although the point estimate for 'Study' is significantly larger. However, (371) notes that zeros in time use data may arise from a mismatch between the reference period of the data (the interview date) and the period of interest, which is typically much longer. He finds that in such a context the marginal effects from Tobit are biased and that only OLS generates unbiased estimates.

[26] I find that the relationship between sunset time and sleep is roughly linear (Figure B.20).

[27] The interaction term is negative and significant, perhaps suggestive of the influence of poverty on sleep as discussed in Section 3.8 as 'child laborer households' tend to be poorer than 'student households'.

[28] In terms of magnitude, an hour delay in sunset time reduces study time by roughly 40 minutes. This is a large effect. I show that later sunset negatively affects study effort on the extensive margin, presumably because tired students are less likely to study at all (Table B.13).

sleep is larger than the increase in marginal product of an extra hour of study effort. In the analytical model, a child chooses to study if the marginal increase in parental rewards from an extra hour of study time is larger than the wage rate ($r\frac{\partial h(H,S)}{\partial H} > W(S)$). These results suggest that labor productivity gains from more sleep are not large enough to induce a student to work. Lastly, a decrease in time allocated to sleep may induce lethargy and increase time allocated to sedentary and compensatory leisure activities. Overall, these results imply that sleep is productivity-enhancing, increasing the marginal returns to study and work effort, for students and child laborers, respectively.

3.5.3 Robustness Checks

The identification assumption underlying this research design is that there exist no district-specific seasonal characteristics that co-vary with time use and intra-annual variation in sunset time at the district level. This may be a strong assumption, one that could plausibly be violated for several reasons, for example, local weather, provincial school calendar, or local festivals. I use three approaches to evaluate the validity of this identification assumption.

First, I control for seasonal observables (e.g., weather) at the district level. There exists considerable seasonal variation in weather patterns across India. Thus, later sunset might be correlated with higher temperatures and precipitation for specific districts. For example, it is plausible that my baseline estimates are confounded by the effects of extreme temperatures on sleep, especially in a context where air conditioning is uncommon. Or if the agricultural calendar (and relatedly the monsoon season) coincides with later sunset for particular districts my estimates could be biased. Table B.14 controls for daily precipitation and temperature at the district level and shows that my estimates remain unaffected.[29][30]

Second, I evaluate effects of later sunset on children's time use for non-school days: weekends. If my estimates were driven by district-specific school calendars, I may not find similar effects for weekends. However, the magnitudes are not significantly different for children's time use over weekends, bolstering the robustness of my findings (Table B.16). This result also suggests that there may be factors that affect children's sleep schedules in addition to school start times.

Third, I control flexibly for district-specific seasonal unobservables by including a suite of interacted fixed effects: state-by-season, latitude-by-week-of-year and district-by-season.[31][32] Separately, these control for seasonal attributes specific to each state, latitudinal zone, and district, respectively. For instance, local festivals that coincide with summer months may increase children's time allocation to leisure and in turn decrease the time allocated to sleep, study effort and work effort. However, Tables B.17, B.18 and B.19 show that although the estimates are noisier, the magnitudes remain relatively unaffected by the inclusion of these fixed effects. Thus, any omitted variables must operate within a season for specific districts.[33]

[29] I use the ERA-Interim daily temperature and precipitation data on a 1 x 1 degree latitude-longitude grid. These data are matched with ITUS at the district-date level.

[30] In addition, controlling for socioeconomic factors at the individual level (e.g., wealth, sex, age) and interview date characteristics (e.g., day-of-week) explains meaningful variation in the outcomes of interest, but my point estimates remain relatively unaffected (Table B.15).

[31] To generate latitude-by-week-of-year fixed effects I divide the country into two arbitrary latitudinal zones using the median latitude and interact indicator variables for each zone with indicator variables for each week-of-year.

[32] The Indian Meteorological Department (IMD) designates four climatological seasons for the country: Winter (December-March), Summer (April-June), Monsoon (July-September), Autumn (October to November).

[33] School summer vacations in India are between April and June. In Table B.20 I drop these months to ensure that my results are not just driven by children's time use during summer

Relatedly, any district-specific seasonal confounders correlated with fixed socioeconomic- or date-related attributes like age, sex, day-of-week, urban status or wealth should be picked up when I include district-by-age-by-season, district-by-sex-by-season, district-by-day-of-week-by-season, district-by-urban-by-season, or district-by-wealth-by-season fixed effects, respectively. For example, if boys are more likely to be engaged in agricultural labor during the monsoon for certain districts, district-by-sex-by-season fixed effects should control for such patterns. These interacted fixed effects fail to meaningfully affect my coefficients of interest (Tables B.24 - B.28).[34]

In sum, these three tests imply that any omitted variable that generates bias in the baseline estimates must i) operate within a season for specific districts, ii) be orthogonal to seasonal observables at the district level, iii) be uncorrelated with district-specific seasonal unobservables that co-vary with fixed observables at the individual or interview date level and iv) persist during both weekdays and weekends. Plausible omitted variables are unlikely to have all of these properties, and therefore my baseline estimates are likely unbiased.[35]

vacations. I find that the coefficients are similar to my baseline estimates apart from the negative effect on 'Work', which is now large and statistically significant. In Table B.21, B.22, and B.23, I drop Winter, Monsoon, and Autumn months, respectively. The point estimates remain unaffected.

[34]In Table B.29 I adjust standard errors to reflect spatial dependence as modeled in (103), and implemented by (202). I allow errors to be spatially auto-correlated within a distance of 500 km. The point estimates remain precisely estimated. Similarly, in Table B.30 I cluster standard errors at the district level to allow errors to be temporally correlated across weeks within a district. The coefficients remain precisely estimated.

[35]If children are more likely to nap on late sunset days than early sunset days due to factors unrelated to the effect of later sunset on (nighttime) sleep, the effects on sleep could be driven by daytime naps and not the other way around. However, in Table B.31 I show that the effects of later sunset on children's time use are robust to dropping 'nappers' from the sample. In Table B.32 I estimate the effects of later sunset using non-linear metrics for sleep duration based on recommendations made by experts in the areas of medicine, physiology and science. I show that an hour delay in sunset significantly reduces the likelihood that children get the recommended amount of sleep (9-11 hours). In Appendix B.2, I show that the effect of later sunset on leisure is driven by indoor and not outdoor leisure.

China Time Use Results

Next, I use the 2004-2009 China Health and Nutrition Survey (CHNS) to examine the effects of later sunset on children's time use in China. Unlike ITUS, CHNS includes information on children's time allocation for a 'typical' or 'usual' day of the year, and not for a particular date. And, although CHNS only provides data on sleep, leisure and homework time, it allows me to investigate the effect of annual average sunset time on children's time allocation.[36] In this setting, I abstract away from seasonal variation in sunset time, only exploiting cross-sectional variation in annual average sunset time.

I estimate the following econometric model:

$$y_{idst} = \beta Sunset_{ds} + \mu_t + \mu_s + \epsilon_{idst} \tag{3.9}$$

Time allocated to sleep, leisure or homework (y), by child i, in district (or county) d, in state (or province) s, in year t, is regressed on annual average sunset time observed in district d in state s to estimate the average effect of an hour's increase in annual average sunset time (β). μ_t are year fixed effects, and μ_s are state fixed effects. Thus, I exploit district-level variation (east to west) in annual average sunset time within a state. Therefore, I control for across province time invariant attributes that are correlated with children's time allocation and annual average sunset time.

An hour delay in annual average sunset time reduces sleep by 0.43 hours (Table B.33). This estimate is remarkably similar to the effect of late sunset on sleep in India, where I exploit intra-annual variation in daily sunset time at the

[36]There exist substantial differences in the definition of leisure between ITUS and CHNS. Furthermore, as a measure of self-investment in study effort, CHNS only provides homework time. These differences are discussed in Appendix B.1.

district level. Furthermore, in line with the ITUS results, I find large positive effects on leisure and negative effects on time spent on homework, although these estimates are noisier.

Because I only exploit cross-sectional variation in sunset time within a state, county level attributes that are correlated with annual average sunset time as well as the outcomes of interest could potentially bias my estimates. For instance, if compared to eastern districts (early sunset), western districts (late sunset) are warmer, then the coefficients might be upwardly biased. In Table B.34, I control for weather and other observables like income, urban status, household size and nutritional intake, that may co-vary with children's time allocation across the east-west gradient within a province, like sunset times. My estimates remain largely unaffected. Indeed, under the strong assumption that these observables are strongly correlated with unobservable confounders, these results indicate that the estimates are unbiased (15; 299).[37]

3.6 Effects of Later Sunset on Academic Outcomes

Using nationally-representative DHS data from 45 countries across the developing world, Figure 3.1 documents a strong negative correlation between annual average sunset time associated with a geographic location and years of schooling among school-age children.[38]

[37] In Table B.35, I show that the effect of later sunset on leisure is driven by indoor and not outdoor leisure.

[38] In successive specifications I control for potential omitted variables – demographics, latitude, elevation, and rural-urban status (Table B.45). I find that the association is robust to controlling for these observables.

However, simple cross-country comparison of children's academic outcomes may be confounded by systematic differences in salient features that covary with annual average sunset time and children's education. To overcome this identification problem, and because my core time use data are from India, I use the geocoded 2015 India DHS to investigate the 'lifetime' or long-run effects of later sunset on educational outcomes for school-age children, exploiting cross-sectional variation in annual average sunset time across eastern and western locations within small administrative divisions, districts. I improve external validity and assess robustness of these results using education data from Indonesia, exploiting a sharp discontinuity in annual average sunset time at the time zone boundary in Kalimantan, Indonesia. Lastly, using an individual level longitudinal panel from Andhra Pradesh, India, wherein the same child is administered comprehensive (low-stakes) tests in math at different dates every survey round, I leverage variation in sunset time at the district-test-date level across survey rounds to evaluate the short-run effects of sunset-induced sleep deficits on children's test scores.

3.6.1 Empirical Model

Using the 2015 India DHS, I estimate the following econometric model:

$$y_{iavd} = \beta Sunset_{vd} + \mu_d + \mu_a + \epsilon_{iavd} \tag{3.10}$$

where y_{iavd} is the outcome of interest for child i of age a in sampling unit v in district d. Outcomes of interest include years of schooling, primary school completion, middle school completion, and enrollment status. Both primary and middle school completion are binary variables that take the value '1' if the child has completed primary and middle school, respectively, and 0 otherwise. Similarly, enrollment status is a binary variable that takes the value '1' if the child is enrolled in school, and 0 otherwise. μ_d are district fixed effects, while μ_a are age fixed effects. District fixed effects control for plausible time invariant omitted variables at the district level. I include age fixed effects to control for differences in grade progression between children of different age groups. Here, I compare the outcomes of children of the same age residing in sampling units with different annual average sunset times within a district. β is the average effect of an hour delay in annual average sunset time, i.e., β is the lifetime effect of an hour delay in sunset time.

The identification assumption underlying this research design is that there exist no omitted variables within a district that co-vary with both annual average sunset times and children's educational outcomes.[39] Lastly, I cluster standard errors at the geocoded sampling unit level as variation in annual average sunset time is at the sampling unit and not at the household level (1).

3.6.2 Results

I find that an hour (approximately two standard deviation) delay in annual average sunset time reduces schooling by about 0.8 years (Table 3.4). A two hour difference in annual average sunset spans the entire width of the country, so another interpretation of the effect size is that a one standard deviation or 25

[39]Residential sorting on sunset time could bias my estimates if such sorting was correlated with annual average sunset and characteristics that affect children's education outcomes. This is relatively unlikely as internal migration is very low in India, both in absolute terms as well as relative to other countries of comparable size and level or economic development (280). In addition, I fail to find evidence for out-migration (in-migration) in locations that observe later (earlier) sunsets (Appendix B.3).

minute delay in annual average sunset time reduces schooling by 0.4 years. This result translates into lower educational attainment at primary and middle school level. That is, a one standard deviation delay in annual average sunset time decreases primary school completion by 5 percentage points, and middle school completion by 4 percentage points. Lastly, an hour delay in annual average sunset time decreases enrollment rates by roughly 11%.[40] These effect sizes are comparable to impacts of larger policy interventions designed to increase schooling in developing countries. For example, in Mexico, childhood exposure to conditional cash transfers through PROGRESA increases schooling by 1.5 years (308). A meta-analysis of 94 studies from 47 conditional cash transfer programs in low- and middle-income countries worldwide finds that the average conditional cash transfer program increases school enrollment by roughly 7% (163).

These estimates are identified by exploiting small variation (up to 10 minutes) in annual average sunset time across the east-west gradient within a district.[41] The underlying assumption when extrapolating the identifying varia-

[40]These point estimates are robust to the inclusion of other observables like elevation, latitude and socioeconomic indicators (Table B.46). The attainment results are also robust to restricting estimation for each tier of education – primary and middle – to the corresponding age-appropriate sample (Table B.47). In Table B.48 I show my results are robust to the use of an alternative indicator for educational attainment: if a child is in primary (secondary) school or has completed primary (secondary) school. I find that an hour delay in annual average sunset reduces the likelihood that school-age children are in primary (secondary) school or have completed primary (secondary) school by roughly 11% (25%). In Table B.49 I show my results are robust to dropping the widest districts in the sample. In Table B.50 I show my results are robust to restricting the sample to include only the widest Indian districts. In Table B.51, I cluster standard errors at the district level to allow errors to be spatially correlated across PSUs within a district. Although the standard errors increase, the point estimates, for the most part, remain precisely estimated. In Tables B.52 and B.53, I show the negative association is present under a less demanding, state fixed effects specification, where I exploit cross-sectional variation in annual average sunset time within a state. Lastly, if younger children (with less completed schooling) are sampled in locations with later annual average sunset, my estimates for years of schooling and educational attainment may be biased. However, I fail to find evidence for such a hypothesis (Table B.54).

[41]Figure B.22 plots the relationship between residualized annual average sunset time and

tion to calculate the effect of an hour delay in sunset time is that the relationship between annual average sunset time and academic outcomes is linear. I find support for such an assumption. First, as mentioned earlier, I find that the effect of sunset time on sleep is roughly linear. Second, results from the longest laboratory-controlled study on the relationship between sleep and cognitive performance indicate that cognition declines linearly with sleep deprivation (411). Third, in Section 3.6.3, I exploit a sharp, one-hour discontinuity in average annual sunset time across locations on either side of the time zone boundary on Kalimantan, Indonesia. I find that the regression discontinuity estimate of the effect of an hour delay in annual average sunset on years of schooling is similar to the India estimate obtained by scaling smaller variation in annual average sunset time.

These are large effects. Therefore, it is important to add context to help interpret these magnitudes. First, it is important to note that these estimates capture the 'lifetime' impacts of later annual average sunset on educational outcomes or the long-term effects of chronic sunset-induced sleep deficits on learning and cognition. Furthermore, my results imply sleep is productivity-enhancing: an hour delay in sunset also reduces time allocated to homework or studying by 40 minutes. (372) estimate an elasticity of academic performance with respect to study time of approximately 0.4.

Second, a series of laboratory experiments that assess the causal effects of

residualized academic outcomes; I show the relationship is roughly linear. Figure B.23 shows the distribution of the difference in annual average sunset time between the easternmost and westernmost locations within a district. We sleep in 90-minute cycles that contain both NREM and REM (rapid eye movement) sleep. First half of the night is dominated by NREM sleep: light NREM (stage 2) sleep is important for memory refreshment while deep NREM (stages 3 and 4) sleep is important for memory consolidation. The second half of the night is dominated by REM (stage 5) sleep, which is important for problem-solving and creativity. Within each cycle, each stage lasts anywhere between 5-15 minutes. Sleep research has shown that just 3 minutes of stage 2 or light NREM sleep improves task performance (194).

short-term sleep loss on cognition find very large effects. The typical elasticity of task performance with respect to sleep duration is approximately four (see (173), for a brief review of short-term causal studies). In Section 3.5, I find that an hour delay in sunset time reduces children's sleep by roughly 30 minutes. If one were to extrapolate, my results suggest that 30 minutes decrease in sleep (one hour delay in annual average sunset time) everyday decreases years of schooling by approximately 0.8 years. Expressed as an elasticity, this estimate is 3.5.

Third, these estimates capture all location-level general equilibrium effects; every child and parent in a location experiences the same, permanent annual average sunset time. Thus, the estimated β includes any spillovers and peer effects from decreasing the mean sleep in a location. (85) estimate an elasticity of academic achievement with respect to peer quality of roughly 0.9. In Section 3.7, I show that later annual average sunset reduces adults sleep as well as earnings. (187) estimates income elasticity of academic achievement of 0.04. (109) estimate an elasticity of family income with respect to child achievement of approximately 2.[42]

Fourth, similarly large effects are observed in two studies that evaluate the consequences of the relationship between sunset time and sleep on adult wages and health outcomes in the US. (173) find a one-hour delay in daily sunset reduces sleep by roughly 20 minutes per week and decreases weekly (short-run) earnings by a statistically significant 0.44%. They also show a one-hour delay in annual average sunset reduces weekly sleep by roughly one hour and decreases

[42]Because I estimate the effect of a quasi-random change in mean sleep in a location, I am unable to identify whose sleep is most important for children's education outcomes: child's own sleep, peers' sleep, or parents' sleep. Prior evidence, discussed above, suggests child's own sleep may have the largest effects on learning outcomes. Moreover, in Section 3.6.3 I show evidence for the short-run importance for child's sleep for learning outcomes.

long-run earnings by 4%. Expressed as an elasticity with respect to sleep duration, their long-run earnings estimate is 2.6. (175) find an hour delay in annual average sunset decreases sleep by roughly 20 minutes per day and increases the likelihood that individuals are obese by 21%.

In Appendix B.3, I use the 2006 Rural Economic and Demographic Survey (REDS), a nationally representative rural sample of Indian households, to control for a rich set of observables (e.g., migration, electricity access, access to roads) in estimating the relationship between annual average sunset and children's education outcomes. I also show household and village level observables do not co-vary with annual average sunset across villages within a district. Moreover, as a complement to the effects on educational outcomes and a robustness check on the underlying conceptual framework, I document a statistically significant negative relationship between annual average sunset time and children's daily wage rate.[43]

3.6.3 Robustness Checks

Indonesia: Regression Discontinuity Estimates

Next, I use the 2003 Indonesian DHS I exploit time zone boundaries in Kalimantan to generate plausibly exogenous variation in annual average sunset time and examine the effects on schooling outcomes for children between 6 and 16 years of age. Kalimantan is the Indonesian portion of the island of Borneo with two time zones: UTC+7 and UTC+8 (Figure B.24). In PSUs lying on the eastern (right) side of the time zone boundary, sunset time occurs an hour later than in

[43] Appendix B.1 describes the REDS data.

nearby PSUs on the western (left) side of the time zone boundary. Thus, school-age children on the later sunset side of the border are more likely to be sleep deprived and have worse educational outcomes.

The first stage is presented in Figure B.25. By construction, I observe a clear discontinuity in annual average sunset time at the border. To estimate the effects on schooling I include age fixed effects to control for differences in grade progression between children of different age groups. My identification strategy rests on the assumption that there are no discontinuities in observable or unobservable variables potentially correlated with outcomes of children of the same age. Indeed, I find that school-age children living in PSUs on the later sunset side are less likely to be enrolled in school, have fewer years of schooling, and relatedly, are less likely to complete primary and middle school. Figure B.26 presents these discontinuities graphically, while Table B.55 presents the formal results. Specifically, school-age children living close to the time zone boundary but on the later sunset side have years of education by 0.72 years fewer years of schooling. This point estimate is remarkably similar to the effects of annual average sunset time on years of schooling for school-age children in India.

I test for the optimal polynomial order by comparing the local linear regression approach with higher polynomial orders, up to the fourth order. Figures B.27 - B.29 show that the point estimates are relatively stable. Next, I evaluate my identification assumption by controlling for a rich set of PSU level geographic and household level socioeconomic indicators. If wealthier households were sorting across the time zone border one would expect these controls to correct the bias emanating from such omitted variables. I control for latitude and elevation as well as wealth, access to electricity and indicator variables for ownership of various assets like television or car. I do not find evidence for any residential sorting as my point estimates remain unaffected (Table B.56). Finally, focusing on outcomes that should not be affected by later sunset I provide a set of placebo tests. Specifically, I find no evidence of discontinuity in children's age, children's gender or household head's age (Table B.57).

The time zone boundary perfectly overlaps with provincial administrative boundaries on Kalimantan, Indonesia. That is, the regression discontinuity design examines differences in children's education outcomes for PSUs closest to the administrative border between West and Central Kalimantan (UTC+7) and South and East Kalimantan (UTC+8). If administrative boundaries are drawn to ensure that economically developed locations fall on a certain side of the time zone boundary then my point estimates may be biased. However, all four provinces followed the Central Indonesian Time or UTC+8 until 1987. West and Central Kalimantan only switched to UTC+7 in 1988.[44] Importantly, to my knowledge, administrative boundaries were not altered during or after this switch. In addition, this means that I can use older cohorts or individuals who completed their education before 1988 (>40 year-olds), under UTC+8, as a placebo sample. As one might expect, I fail to find evidence for a statistically significant discontinuity in years of schooling at the time zone border for individuals over 40 years of age (Figure B.30 and Table B.58).

[44]West Kalimantan followed UTC+7.5 between 1945 and 1963, with the exception of a brief period between 1948 and 1950 when the province followed UTC+8. West Kalimantan switched to UTC+8 in 1964.

Test Scores

Here, I use an individual level longitudinal panel from Andhra Pradesh, India, the 2002-2013 Young Lives Survey (YLS), and show that later sunset is negatively associated with children's test scores.[45]

The impacts of later sunset on academic progression are mediated through the effect of sunset-induced sleep deficits on learning and cognition. Thus, children exposed to later sunsets may also have lower test scores. To provide evidence for this hypothesis, I use comprehensive (low-stakes) tests administered in YLS, and examine the effect of later sunset on math scores for school-age children. The study followed two cohorts of children, born in 1994/95 and 2001/02, respectively, over a period of more than 10 years. Children between the ages 5 and 19 were administered comprehensive tests in math at regular intervals between 2002-2014. Unlike DHS, YLS is conducted in a single state in India, Andhra Pradesh, and only provides district-level identifiers. Given these features of the YLS data, I exploit both cross-sectional variation in annual average sunset time at the district level as well as seasonal variation in daily sunset time at the district-test-date level to estimate the effects of long- and short-term sleep deprivation on math test scores, respectively.

First, I estimate the impact of long-term or chronic sunset-induced sleep deficits on test scores. I compare test scores of children of the same age residing in districts with different annual average sunset times within the state of Andhra Pradesh. I show that children residing in districts with later annual average sunset times have lower test scores. A one hour delay in annual average sunset time (approximately two standard deviation) is associated with

[45] I briefly describe the YLS data in Appendix B.1.

a 0.8 standard deviation decrease in math scores (Table B.59). Controlling for latitude and weather does not affect the point estimate. If district-specific unobservables, that are correlated with children's test scores, co-vary with annual average sunset time across eastern and western districts within Andhra Pradesh, then these estimates may be biased.[46] Because YLS does not provide village/city block identifiers, I am unable to exploit within-district cross-sectional variation in annual average sunset time.[47]

Next, I examine the impacts of short-term sleep deprivation on math scores. Because the same child is tested at different dates every survey round, I exploit seasonal variation in sunset time at the district-test-date level after absorbing fixed child-specific confounders via lagged test scores or child fixed effects. I control for seasonal confounders common across all children in the sample via week-of-year fixed effects. I find an hour delay in sunset time on the day of the test reduces children's test scores by 0.5 standard deviation (Table B.60).[48] I control for potential omitted variables using lagged test scores as a proxy for child-specific unobservables (e.g., ability) that plausibly co-vary with daily sunset time and educational output. It is reassuring that controlling for lagged test scores explains meaningful variation in subsequent test scores, but does not affect the sunset-test score relationship. Moreover, although the point estimate is noisily estimated, I show that the short-run impact of sunset time on test scores is robust to the inclusion of child fixed effects.[49] The short-run impacts of later

[46]Figure B.31 presents binned scatterplots for the relationship between residualized annual average sunset time and residualized math test scores; I show the relationship is roughly linear.

[47]The comparison of India DHS estimates under state vs. district fixed effects specification suggest that these estimates may be biased downwards. Moreover, districts in western Andra Pradesh are close to two leading economic centres of India: Bangalore and Hyderabad.

[48]This estimate should not be interpreted as the single day effect of later sunset on test scores; sunset time on the day of the test is strongly correlated with sunset time observed days or weeks prior to the test date.

[49]Figure B.32 presents binned scatterplots for the relationship between residualized daily sunset time and residualized math test scores; I show the relationship is roughly linear. As a falsifi-

sunset are comparable to the short-run effects of later school start times on test scores. For example, (86) find that a start time of 7 am reduces test scores for a course taught in the first period class by 0.15 standard deviation while a 7.50 am start time has no effect on test scores. Furthermore, with a 7 am start time students performed significantly worse (-0.10 standard deviation) even in subsequent classes, suggesting poor performance throughout the day.

3.7 Effects of Later Sunset on Adults' Time Use and Wages

Many studies have shown that both parental money and time investments are important for children's human capital production (104; 105; 158). As an additional channel, later sunset may affect children's education production by decreasing adults' wages, and consequently parental investment in children's human capital (215; 220; 254; 403).

Later sunset may reduce adults' sleep duration, and depending on how adults trade-off sleep with work, home production and leisure, later sunset may affect monetary and time investments in children's education. If labor markets are competitive, workers are paid their marginal revenue product, and sleep is more work-productivity enhancing than home-productivity enhancing, later sunset may reduce sleep and wages, disincentivizing work effort but increasing time allocated to home production. In such a scenario, later sunset may reduce

cation test, in Table B.61 I show sunset time on the previous survey round test date and sunset time on the next survey round test date do not affect children's math scores in the current survey round.

household expenditure on children's education but increase parental time investment in children. On the other hand, if sleep is more home-productivity enhancing than work-productivity enhancing, later sunset will reduce time allocated to home production but increase time allocated to labor activities.

To test these hypotheses, I estimate the baseline ITUS specification (Equation 8) and examine the effects of later sunset on adults' time allocation. I find that an hour delay in sunset time reduces adults' sleep and work effort by 30 minutes, but increases time allocated to home production and leisure (Table 3.5). However, I fail to find evidence for an effect on parental time investments in children. The magnitude is smaller than 5 minutes and statistically insignificant.[50][51]

Next, I estimate the baseline DHS specification (Equation 10) using data from the Rural Economic and Demographic Survey (REDS), and evaluate the effect of later annual average sunset on adults' daily wage rate. That is, I compare the prevailing wage rate among adult daily wage laborers who reside in villages with different annual average sunset time within a district. In line with the effects on time use, an hour delay in annual average sunset reduces adult wage rate by INR 8. Although the point estimate both males and females is negative, the effect on male wage rate noisier (Table 3.6).[52] Overall, an hour delay in

[50]I do not find evidence for a significant relationship between later sunset and time spent with children even when restricting the sample to households with school-age children, households with younger children, or households with multiple children (Table B.72).

[51]In Tables B.73-B.75, I control flexibly for district-specific seasonal unobservables that may be correlated with both adults' time use and sunset time by including a suite of interacted fixed effects: state-by-season, latitude-by-week-of-year and district-by-season. I find the point estimates for the effect of later sunset on sleep and leisure are relatively unaffected by the inclusion of these fixed effects. However, the coefficient on time allocated to work is now roughly zero. This may reflect the presence of downward nominal wage rigidities in village labor markets in the face of transitory negative shocks (228).

[52]Rural markets for hired labor in India are active with most households buying and/or selling labor (36; 329). Labor is typically traded in decentralized markets for casual daily workers. In fact, 98% of agricultural wage employment is through casual wage contracts (228). Within a village, there is typically a sex-age-specific wage for casual daily labor for any given task (58; 138; 328). Minimum wage policies are in practice ignored and there is little government in-

sunset is associated with a decrease of roughly INR 2,500 (INR 8 x 312 working days) or USD 40 in annual earnings of a rural daily wage worker.[53][54]

3.8 Can Poverty Help Explain Why Households Fail to Adjust?

If sleep is productivity-enhancing, why don't families adjust their sleep schedules when the sun sets later? Investigating the determinants of such an adjustment failure, and not just the reduced form impacts, is necessary for effective policy design. In this section, I investigate if poverty helps explain why households fail to adjust to later sunset.

Poverty may impede adjustment in two ways. First, the sleep environment in developing countries is associated with noise, heat, mosquitoes, overcrowding, and overall uncomfortable physical conditions (180; 310), and unlike the non-poor, the poor may simply lack the financial resources to invest in sleep-inducing goods (e.g., window shades, separate rooms, indoor beds, food) and adjust their sleep schedules when the sun sets later. Second, poverty may cause stress and negative affective states, such as depression, impede cognitive func-

tervention in the private wage labor market (329; 330). Therefore, these point estimates capture the effect of a fixed (time-invariant) feature – annual average sunset time – associated with a village on the prevailing gender-specific wage rate.

[53] Because I fail to find evidence for a significant relationship between sunset time and adults' work hours under more demanding econometric specifications, any decrease in wages likely results from wage changes due to the productivity impacts of sleep, rather than changes in hours worked.

[54] By increasing dropouts, later sunset may increase the supply of child labor at the village level, in turn reducing adults' wage rate. Because the estimates are at the village level I cannot rule out such a general equilibrium effect. In addition, these wage effects might also be mediated by the childhood impacts of later sunset on education production.

tion by consuming mental resources or through reduced food intake, all of which affect decision-making (65; 112; 191; 259; 342; 347; 354; 367).[55] Therefore, psychological considerations associated with poverty may make it harder to assess one's own sleep-productivity relationship and optimize sleep schedules when the sun sets later. On the other hand, the non-poor, by the virtue of owning these physical and psychological goods, may be better able to adjust their sleep schedules when the sun sets later.

To explore this hypothesis, I use ITUS and examine the heterogeneous impacts on sleep by correlates of poverty or socioeconomic status: type of house structure (temporary vs. permanent), rural vs. urban status, education, and average monthly household expenditure.[56] I find households that reside in a temporary structure get less sleep on later sunset days compared to households that reside in a permanent structure (Table 3.7). The interaction term is statistically significant and exacerbates the level effect by 25% (7 minutes). The negative effect of later sunset on sleep is significantly (8 minutes) larger for less-educated individuals. The impact of an hour delay in later sunset is almost 11 minutes larger for rural households compared to urban households. Lastly, the negative effect of later sunset on sleep is significantly larger for households with average monthly expenditure less than that of the 75th percentile household compared to households above the 75th percentile household; sunset-induced sleep deficits are largest for households with average monthly expenditure below the

[55] Several medical studies have linked poverty with elevated levels of the stress hormone cortisol and poor cognitive function in children (94; 132; 151; 252; 253; 266; 290; 340).

[56] Average monthly expenditure for households that reside in permanent structure is INR 3,500 compared to roughly INR 2,000 for households that reside in a temporary structure. Similarly, average monthly expenditure among rural households is INR 2,200 compared to INR 3,600 among urban households. While average monthly household expenditure for individuals who have at least primary education is INR 3,100 compared to INR 2,100 for individuals who are illiterate or have not completed primary school.

25th percentile.[57] Overall, these results suggest that socioeconomic status (SES) plays an important role in explaining sunset-induced sleep deficits.

However, it is plausible that these interaction effects are confounded by omitted variables that are correlated with socioeconomic status, particularly for adults. For instance, if low-SES individuals are disproportionately employed in occupations with formal work start times, it is possible that the interaction effect reflects morning work constraints rather than poverty;[58] unlike self-employed high-SES individuals (e.g., agricultural cultivators), low-SES individuals or daily wage workers (e.g., agricultural laborers) may fail to compensate for later bedtimes – due to later sunset – by waking up later. Therefore, I exploit quasi-experimental variation in income around the harvest period to present a plausibly causal relationship between poverty and sunset-induced sleep deficits.

3.8.1 Empirical Model

My research design compares the effects of later sunset on sleep allocation before harvest, when crop cultivator households are poorer, with after harvest, when richer. Crop cultivator households in India receive much of their annual income at harvest time or shortly after and are unable to smooth consumption over states of nature and across time (114; 124; 316; 331; 334; 407). (259) show

[57]These heterogeneous impacts are of similar magnitudes among both children and adults (Table B.77).

[58]In Table B.78 I examine the heterogeneous impacts on children's time use by electrification status, as proxied by district-level annual average nighttime lights. I find the negative effect of later sunset on sleep and study time are significantly larger for children in districts with poor electricity access. This may be consistent with an explanation where high-SES households have better electricity access, facilitating adjusted sleep when the sun sets later. Because sleep is productivity-enhancing, it also increases study effort.

farmers in India show diminished cognitive performance and higher stress levels before harvest as compared with after harvest. They also show pre-harvest poverty reduces cognitive capacity as poverty-related concerns consume mental resources. Thus, financial and psychological considerations associated with pre-harvest poverty may induce unadjusted, sub-optimal sleep when the sun sets later.

For the main analysis, I restrict the ITUS sample to individuals from households whose primary source of income is agricultural cultivation, comparing the effect of later sunset on sleep between the pre- and post-harvest period. India has two agricultural seasons, and the agricultural calendar for each state varies by crop. Therefore, for both agricultural seasons in each of the six states in ITUS, I define pre- and post-harvest month according to the agricultural calendar for the main crop grown in each state during a particular agricultural season.[59] Because harvest calendars vary across locations and seasons, I also include calendar and location fixed effects, controlling for all fixed differences between time periods and districts.[60]

[59]India's first agricultural season is the kharif season, and broadly the growing season lasts from June through October and harvest from October through November. While the second agricultural season in India is called rabi, and broadly the growing season lasts from October through March and harvest from April through May. In Appendix B.5, I describe the pre- and post-harvest months for both agricultural seasons for all 6 states in ITUS.

[60]Figure B.33 presents the relationship between the pre-post harvest periods and sleep among crop cultivator households in the raw data. As expected, crop cultivator households allocate less time to sleep in the pre-harvest period compared to post-harvest period. It also presents the relationship between the pre-post harvest periods and time allocated to crop sale (and purchase) related activities in the raw data. Unfortunately, ITUS does not provide time use separately by crop sale and purchase related activities. I find no crop sale (and purchase) related activity in the first two weeks of the pre-harvest period. And as one might expect, crop sale (and purchase) related activity increases towards the end of the pre-harvest period. Importantly, most of sale (and purchase) related activity takes place in the post-harvest period.

I estimate the following econometric model:

$$\begin{aligned} y_{idwt} = &\beta_1 Sunset_{dwt} + \beta_2 PreHarvest_{dw} \\ &+ \beta_3 Sunset_{dwt} * PreHarvest_{dw} + \mu_w + \mu_d + \epsilon_{idwt} \end{aligned} \tag{3.11}$$

where y_{idwt} is time allocated to sleep by individual i, in district d, on date t, during week-of-year w. $Sunset_{dwt}$ is sunset time observed by that individual i, in district d on date t. $PreHarvest_{dw}$ is the state-specific indicator equal to 1 if week w is the pre-harvest period for district d, 0 otherwise. I also control for district (μ_d) and week-of-year (μ_w) fixed effects. My coefficient of interest is the interaction between the indicator variable for pre-harvest month and daily sunset time (β_3). It captures the effect of pre-harvest poverty on sleep by comparing the difference in sleep duration between late sunset days and early sunset days during the pre-harvest period with the difference in sleep duration between late sunset days and early sunset days during the post-harvest period.

The identification assumption underlying this econometric strategy is that there is no time-varying district-specific confounder that differentially affects sleep on only later sunset days during the pre-harvest month. I evaluate the validity of this assumption through various falsification and robustness checks.

Lastly, because pre- and post-harvest months only include four months of data corresponding to two agricultural seasons, the week-of-year specification may absorb significant identifying variation in daily sunset times. Therefore, I also estimate econometric models that instead include season or month fixed effects. As before, standard errors are clustered at the district-week level.

3.8.2 Results

Table 3.8 shows that the negative effect of later sunset on sleep is significantly larger before harvest (interaction effect). In fact, almost the entire effect of later sunset on adults' sleep seems to be associated with pre-harvest poverty. That is, an hour delay in sunset time during the pre-harvest period decreases adults sleep by roughly 25 minutes, but the effect of later sunset during the post-harvest period (the level effect) is closer to zero. As adult crop cultivators are self-employed, and not constrained by start times for work, sunset-induced sleep deficits for adult crop cultivators are largely driven by considerations related to poverty. However, as one might expect, both the level and interaction effects are economically meaningful for school-age children, who unlike adult cultivators face other constraints – e.g., school start times – in addition to poverty.[61][62] Importantly, although the point estimates are not always precisely estimated, the magnitude of the interaction term (and the level effects for children) is statistically indistinguishable across specifications. Overall, for individuals with formal morning start time constraints – school-age children from crop cultivator households – pre-harvest poverty explains about a quarter of the effect of later sunset on sleep. But for individuals that don't have formal work start time constraints – adults from crop cultivator households – the entire effect of later sunset on sleep is driven by the period when the household is poor

[61] In Table B.79 I provide evidence that although adult cultivators delay bedtimes on later sunset days during the post-harvest period, they are able to compensate by waking up later. On the other hand, during the pre-harvest period, adult cultivators go to bed even later on late sunset days; moreover, they are less able to compensate by waking up later. While children from crop cultivator households fail to adjust to later bedtimes by waking up later on later sunset days, both before and after harvest. But during the pre-harvest period children are less able to compensate by waking-up later on late sunset days, exacerbating effects of later sunset before harvest.

[62] As one might expect, the lack of level effects for adult crop cultivators are driven by farmers with no children. I find that the level effect is negative for farmers with school-age children (Table B.80).

(pre-harvest).

3.8.3 Robustness Checks

There is more agricultural work to be done in the pre-harvest period. If crop cultivator households work longer hours when the sun sets later during the pre-harvest month, because they have more daylight, and this increase in work effort is correlated with sleep, then the interaction effect (β_3) may be explained by more daylight or an increase in work hours instead of 'pre-harvest poverty'. Therefore, I control for possible changes in hours worked by crop-cultivator cultivators on later sunset days (Table B.81). The interaction effect remains unaffected, suggesting that any changes in work hours do not explain the decrease in sleep during the pre-harvest period compared to the post-harvest period.[63]

Next, because non-cultivator households do not depend on lumpy harvest income and have other, stable sources of income, I use non-cultivator households as a falsification test. I fail to find evidence for pre-harvest period effects for individuals from non-cultivator households (Table B.83). The interaction effects are not statistically significant or economically meaningful. However, as expected, the level effects of later sunset on sleep for adults from non-cultivator households, either employed in urban locations or working as daily wage laborers in rural locations, are economically and statistically significant.[64] In addition, as before, the level effects of later sunset on sleep for school-age children are economically significant and statistically indistinguishable across specifica-

[63]Furthermore, in Table B.82 I show controlling for daylight duration does not have a significant effect on the magnitude of the interaction term.

[64]In Table B.84 I show that adults from non-cultivator households are unable to compensate for later bedtimes due to later sunset by waking up later both before and after harvest.

tions.

I implement another falsification test using non-cultivator households whose primary source of income is agricultural labor. Daily wage agricultural laborers perform the same tasks as crop cultivators during the pre-harvest month – e.g., land clearing, weeding, threshing and harvesting etc. – but unlike crop cultivators, who depend on lumpy harvest income, agricultural laborers are paid daily wages for these services throughout the agricultural season.[65] Thus, agricultural laborers are not poorer before harvest compared to after harvest. In fact, agricultural laborers might be poorer after harvest because there may be less agricultural work available during the post-harvest month: in the post-harvest period they increase work hours in non-agricultural sectors (Table B.85), however, total work hours for an individual from the average agricultural laborer household declines slightly. Overall, agricultural laborers are significantly poorer in terms of absolute wealth than cultivator households.[66] Even so, Table B.86 fails to find evidence that effect of later sunset is larger before harvest compared with after harvest for agricultural laborers. The interaction term is positive but not statistically significant. The existence of a significant pre-harvest effect among richer cultivator households and an insignificant pre-harvest effect among poorer agricultural laborer households is consistent with the explanation that the interaction term arises from financial and psychological considerations related to liquidity constraints, precisely as one would expect.

Interestingly, the level effects for agricultural laborers are economically and

[65] Agricultural wage contracts in Indian rural labor markets are typically bilaterally arranged between employers and workers and are of short duration, usually one day (138; 228).

[66] The average monthly household expenditure among agricultural laborers is roughly INR 1,605, compared to INR 2,240 among other non-cultivators. Similarly, while agricultural laborers have negligible landholdings, the average landholdings among cultivator households is 3.5 acres.

statistically large. This may either be because of other constraints on sleep in the form of work start times or material and mental constraints related to poverty. To explore this further, I compare level effects between agricultural laborers and other non-cultivator households. Both sets of individuals likely face some manner of structured work schedule, but agricultural laborers are much poorer than other non-cultivators on average.[67] I find that the level effects among agricultural laborers are economically larger compared to other non-cultivators, perhaps again suggesting that considerations associated with poverty are at least partially responsible for sub-optimal sleep on later sunset days among poorer households like agricultural laborers.

Lastly, using the sample of crop cultivator households, I estimate a triple-difference research design by adding interactions between an indicator variable for wealth, $Richer_{idwt}$, and $Sunset_{dwt}$, $PreHarvest_{dw}$ and $Sunset_{dwt} * PreHarvest_{dw}$ to Equation 11. $Richer_{idwt}$ is equal to 1 if individual i belongs to a household with average monthly household expenditure greater than that of the median household in the sample, 0 otherwise. The identification assumption for the triple-interaction term is that there is no time-varying district-specific confounder that differentially affects sleep of only richer crop cultivator households on late sunset days during the pre-harvest month. As before, individuals lose significantly more sleep before harvest, when poorer, that after harvest, when richer (Table B.87). However, as one would expect, these interaction effects are economically smaller for individuals from richer households. Together these results suggest a causal effect of poverty on sleep.

[67]The average monthly household expenditure among other non-cultivators is roughly INR 3,170, almost 100% greater than agricultural laborers.

3.9 India-Wide Human Capital Costs

Emerging out of the British Empire in the mid-20th century, India reckoned a single time zone would serve as a unifying force, and adopted the Indian Standard Time or IST (UTC+5.5) across her territorial boundaries. However, India measures 3,000 km from east to west, spanning roughly 30° longitude, corresponding with a two-hour difference in mean solar time.[68] That corresponds roughly to New York and Utah sharing one time zone, but with a billion more people, of whom 200 million live below the USD 1.90-a-day poverty line (402). In such a context, individuals in western India may begin sleep later than those in eastern India due to the relationship between the timing of sunset and bedtime, but fail to compensate by waking up later as India uniformly follows a standard time zone, resulting in potentially large implications for human capital production across the east-west gradient, ceteris paribus.

To generate India-wide, back-of-the-envelope human capital costs, I use the point estimate of the effect of a one-hour difference in annual average sunset time on adults' wages as it plausibly includes both the life-cycle impacts on human capital production as well as the contemporaneous effects on worker productivity. Importantly, for each district I compute estimates relative to the central meridian. The meridian passing through at 82.5° E is the central meridian for India. Thus, clocks across the country are set to the solar noon of the central meridian, but clock noon corresponds to solar noon only at 82.5° E. But, residents west of 82.5° E are ahead of the solar clock (late sleepers), while residents east of the central meridian are behind the solar clock (early sleepers) (Figure B.37(a)).[69] Therefore, I compute the following equation for each district

[68]Figure B.35 shows the spatial variation in annual average sunset times across India.

[69]Thus, the point estimate of a one-hour difference in annual average sunset time can also be

i:

$$HumanCapitalCosts_i = -8 * 312 * Population_i * (MeanSolarTime_i - IST) \quad (3.12)$$

where INR −8 is the point estimate for adults' wages and 312 are the number of working days in a year as per the ITUS data. While $Population_i$ is the population of adults at the district level and $MeanSolarTime_i - IST$ is difference between the district-specific annual average sunset time and the annual average sunset time at 82.5° E.

The countrywide estimate is calculated as follows:

$$HumanCapitalCosts_{India} = \sum_{i=1}^{N} HumanCapitalCosts_i \quad (3.13)$$

where N is the total number of districts in the country.

I find that India incurs annual human capital costs of roughly 4.1 billion USD or 0.2% of India's nominal GDP due to the existing policy regulating time zone boundaries in the country.[70] This is a significant number as India's education expenditure is less than 3% of the GDP (145). Moreover, note that this net estimate masks substantial spatial heterogeneity. I find that while highly-populated western districts incur large human capital costs, while their counterparts in the east accrue substantial gains (Figure B.37(b)).

These estimates are calculated against an unrealistic counterfactual of continuous time zones across India. Therefore, I also calculate human capital costs associated with the existing time zone policy against the counterfactual of a two time zone policy: UTC+5 for western India and UTC+6 for eastern India, where

interpreted as the effect of a one-hour difference between mean solar time and clock time.

[70] Using the 95% confidence interval for the point estimate on adults' wages, the lower and upper bounds for these human capital costs are roughly 2 million USD and 6 billion USD, respectively.

western (eastern) India includes districts to the left (right) of 82.5° E, and the meridian passing through 75° E (90° E) defined as its central meridian. In fact, this counterfactual is precisely what was intended by the worldwide standard time zone scheme at conception (51). Figure B.37 calculates human capital costs associated with this hypothetical time zone policy against the counterfactual of continuous time zones. While Figure B.38 presents estimates for human capital costs associated with the existing time zone policy – UTC+5.5 – compared to this hypothetical counterfactual – UTC+5/UTC+6. Interestingly, the net human capital costs of this hypothetical policy compared to the counterfactual of continuous time zones are positive, albeit small (+100 million USD). Therefore, the net human capital gains associated with a switch to the realistic two time zones policy – UTC+5/UTC+6 – are comparable to the gains from a switch to the unrealistic continuous time zones policy. That is, India would incur annual human capital gains of over 4.2 billion USD if she switches from the existing time zone policy to the proposed two time zone policy.

The assumption underlying these calculations is that daily schedules fail to adjust to differences between solar time and clock time. This is a strong assumption. I evaluate it in four ways. First, a review of the existing literature suggests that work schedules are unaffected by solar cues instead responding to uniform policy choices at the federal or state level (173; 175; 185). Second, as shown above, in India, individuals fail to compensate for sunset-induced delays in bed time by waking up later. Third, I find that school schedules fail to adjust to sunset times across the east-west gradient (Table B.88). Fourth, reports in the popular press indicate that work hours for government offices across the country do not respond to solar cues.[71]

[71] The Chief Minister of Arunachal Pradesh, a state in the northeast, is quoted as saying, *"Several daylight hours are wasted as government offices open only at 10 am."* Meanwhile, the Chief Min-

There may be benefits associated with the synchronization of daily schedules across the country,[72] and one must be cautious about proposing changes to the existing time zone policy without a thorough cost-benefit analysis. In Appendix B.7, I also explore two other policy interventions that may mitigate the effects of later sunset on children's education outcomes: (i) later school start times and (ii) social protection programs. I find suggestive evidence that later school start times allow children to compensate for later bedtimes by waking up later, and attenuate the effect of later sunset on schooling outcomes. Meanwhile, each additional year of exposure to a conditional cash transfer program mitigates the effect of later sunset on children's test scores.

3.10 Conclusion

In this paper, I provide evidence that arbitrary clock conventions – by generating large discrepancies in when the sun sets across locations – help determine the geographic distribution of educational attainment levels. I establish four results. First, later sunset reduces children's sleep: when the sun sets later, children go to bed later; by contrast, wake-up times are not regulated by solar cues. Sleep-deprived students decrease study effort, consistent with a model where sleep is productivity-enhancing and increases the marginal returns of effort.

ister of another northeastern state, Assam, proposed advancing working hours in the state, *"The sun rises here earlier than rest of the country and we can start our work half an hour earlier, from 9.30am."* (e.g., (285; 385; 387; 392))

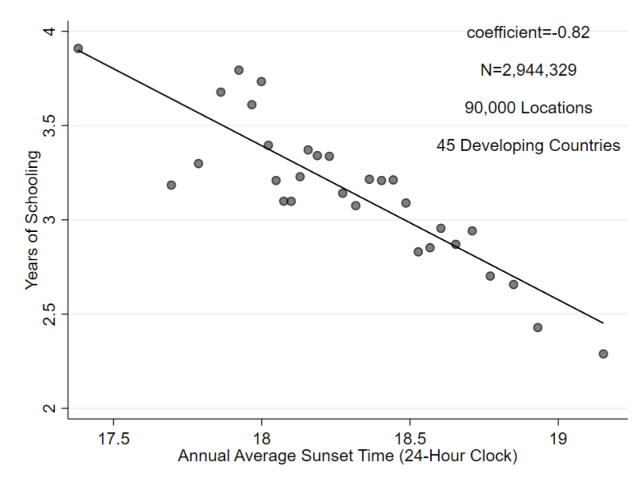
[72]For instance, employing bilateral data on FDI stock from the OECD direct investment statistics, (370) show time zone difference reduces bilateral Foreign Direct Investment (FDI) stock. Using data on bilateral trade among individual states of the US and individual provinces of Canada, where cultural, economic, institutional, and geographical determinants of trade are much more homogeneous than in cross-country studies, (148) find time zone differences reduce bilateral trade. However, in both studies the effects are non-linear; time zone differences of less than 4 and 1.5 hours do not matter for bilateral FDI and trade, respectively.

Second, sunset-induced sleep deficits have significant negative effects on academic outcomes; school-age children exposed to later sunsets attain fewer years of education, are less likely to complete primary and middle school, are less likely to be enrolled in school, and have lower test scores. Third, later sunsets are also associated with fewer hours of sleep and lower wages among adults. Fourth, the non-poor adjust their sleep schedules when the sun sets later; the negative effects of later sunset on sleep are most pronounced among the poor, especially in periods when households face severe financial constraints.

3.11 Tables and Figures

3.11.1 Figures

Figure 3.1: Annual Average Sunset Time and Children's Education in the Developing World



Notes: This figure presents a binned scatterplot and linear fitted values for the raw relationship (correlation) between years of schooling and annual average sunset time for children between 6 and 16 years of age across the developing world. Data on years of schooling is obtained from nationally representative surveys conducted by the Demographic and Health Survey (DHS). I assembled and harmonized all DHS datasets collected through 2016 for which latitude and longitude of the primary sampling unit (PSU) or cluster was recorded allowing me to generate annual average sunset time at the PSU level. That is, I use the universe of DHS data with geolocation information from Latin America, Africa, South Asia, and Southeast Asia: 90,000 locations in 45 countries. The 45 countries include Angola, Bangladesh, Benin, Burkina Faso, Burundi, Cambodia, Cameroon, Chad, Colombia, Comoros, Democratic Republic of the Congo, Dominican Republic, East Timor, Egypt, Ethiopia, Ghana, Guatemala, Guinea, Haiti, Honduras, India, Indonesia, Ivory Coast, Kenya, Lesotho, Liberia, Malawi, Mali, Morocco, Mozambique, Myanmar, Namibia, Nepal, Niger, Nigeria, Pakistan, Peru, Philippines, Rwanda, Senegal, Sierra Leone, Uganda, United Republic of Tanzania, Zambia and Zimbabwe.

3.11.2 Tables

Table 3.1: Effect of Late Sunset on Bedtime and Wakeup Time (Hours)

	(1) Bedtime β / SE	(2) Wake-up Time β / SE
Sunset Time (Hours)	0.36***	-0.13
	(0.10)	(0.08)
District FE	Yes	Yes
Week-of-Year FE	Yes	Yes
Mean	21.33	6.43
Observations	13863	13911
R^2	0.178	0.250

Notes: This table presents the effect of daily sunset time on bedtime and wakeup time for children between 6 and 16 years of age on weekdays in India. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects. I generate bedtimes using ITUS for all children who started sleep between 6 pm and 12 am such that they slept continuously for at least two hours. While wake-up times are generated for all children who ended sleep between 4 am and 10 am such that they were continuously awake for at least two hours. Unfortunately, this means that I am unable to generate bedtimes (wakeup times) for 101 (53) school-age children out of the 13,964 in the entire sample. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table 3.2: Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE
Sunset Time (Hours)	-0.47***	-0.67***	1.65***	0.10
	(0.14)	(0.24)	(0.41)	(0.33)
District FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	9.07	1.50	7.60	2.05
Observations	13964	13964	13964	13964
R^2	0.091	0.169	0.294	0.070

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure and work (in hours) by children between 6 and 16 years of age on weekdays in India. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table 3.3: Effect of Late Sunset on Children's Time Use by Primary Activity (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE
Sunset Time (Hours)	-0.44***	-0.88***	2.03***	0.21
	(0.14)	(0.24)	(0.41)	(0.26)
Sunset Time*Worker	-0.11**	0.82***	-1.36***	-0.69***
	(0.06)	(0.08)	(0.20)	(0.17)
District FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	9.07	1.50	7.60	2.05
Observations	13964	13964	13964	13964
R^2	0.091	0.342	0.321	0.477

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure and work (in hours) by children between 6 and 16 years of age on weekdays in India. Each column represents a separate regression estimating Equation (8) on the outcome variable with an interaction term between daily sunset time and child's primary activity; the interaction term captures the effect of an hour delay in daily sunset time for child laborer compared to a student. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table 3.4: Effect of Late Sunset on Years of Schooling, Educational Attainment, and Enrollment Status

	(1) Years of Schooling β / SE	(2) Primary (0/1) β / SE	(3) Middle (0/1) β / SE	(4) Enrolled (0/1) β / SE
Annual Average Sunset Time (24-Hour Clock)	-0.86***	-0.13***	-0.08**	-0.11**
	(0.31)	(0.04)	(0.03)	(0.05)
Age FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Mean	4.44	0.48	0.21	0.90
Observations	638682	638682	638682	638682
R^2	0.732	0.643	0.561	0.093

Notes: This table presents the effect of annual average sunset time on years of schooling, likelihood of completing primary (0/1) and middle school (0/1), and enrollment status (0/1) for children between 6 and 16 years of age in India. Each column represents a separate regression estimating Equation (10) on the outcome variable. All regressions include age and district fixed effects. Standard errors are in parentheses, clustered at the PSU level. Source: 2015 India DHS.

Table 3.5: Effect of Late Sunset on Adults' Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE	(5) HH Chores β / SE	(6) Time With Kids β / SE
Sunset Time (Hours)	-0.50***	-0.03	0.90***	-0.56***	0.21*	0.08
	(0.10)	(0.03)	(0.21)	(0.21)	(0.12)	(0.05)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean	8.11	0.11	7.06	5.40	2.72	0.43
Observations	48804	48804	48804	48804	48804	48804
R^2	0.078	0.012	0.044	0.026	0.018	0.022

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure, work, home production and time spent with children by individuals (in hours) over the age 16 on weekdays in India. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table 3.6: Effect of Late Sunset on Adults' Daily Wage Rate

	(1) Adult Wage (INR) β / SE	(2) Male Wage (INR) β / SE	(3) Female Wage (INR) β / SE
Annual Average Sunset Time (Hours)	-8.03**	-3.92	-13.98**
	(3.69)	(3.91)	(5.81)
District FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Place FE	Yes	Yes	Yes
Geographic Controls	Yes	Yes	Yes
Mean	63.97	67.49	49.66
Observations	6055	5952	2491
R^2	0.592	0.612	0.550

Notes: This table presents the effect of annual average sunset time on adult's daily wage rate by industry at the village level in India. Each column represents a separate regression; all regressions include district, industry and place (inside or outside the village) fixed effects, and geographic controls: latitude, rainfall, temperature and elevation. Daily wage rates are winsorized at the 1% level. Standard errors are in parentheses, clustered at the village level. Source: REDS.

Table 3.7: Heterogeneity by Correlates of Poverty: Effect of Late Sunset on Sleep (Hours)

	(1) Sleep β / SE	(2) Sleep β / SE	(3) Sleep β / SE	(4) Sleep β / SE
Sunset Time (Hours)	-0.44***	-0.39***	-0.42***	-0.43***
	(0.10)	(0.10)	(0.10)	(0.10)
Sunset Time*Temporary House Structure (0/1)	-0.11***			
	(0.04)			
Sunset Time*Rural (0/1)		-0.19***		
		(0.05)		
Sunset Time*No Primary Education (0/1)			-0.13***	
			(0.03)	
Sunset Time*HH Expenditure∈(50p,75p)				-0.09*
				(0.04)
Sunset Time*HH Expenditure∈(25p,50p)				-0.08**
				(0.04)
Sunset Time*HH Expenditure∈(0p,25p)				-0.17***
				(0.05)
District FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	8.33	8.33	8.33	8.33
Observations	62768	62768	62768	62768
R^2	0.073	0.075	0.075	0.072

Notes: This table presents the heterogeneous effect of daily sunset time on time allocated to sleep by correlates of socioeconomic status on weekdays for all individuals over the age of 6 in India. Each column represents a separate regression. Column 1 shows the effect of daily sunset time on sleep for households that live in a temporary house structure compared to households that live in a permanent house structure. Column 2 shows the effect of daily sunset time on sleep for households living in rural areas compared to households living in urban areas. Column 3 shows the effect of daily sunset time on sleep for individuals that have completed primary education compared to individuals that have not completed primary education. Column 4 shows the effect of daily sunset time on sleep for households with average monthly expenditure below the 25th percentile, between 25th and 50th percentile, and between 50th and 75th percentile, compared to households with average monthly expenditure above the 75th percentile. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table 3.8: Crop Cultivator Households: Effect of Late Sunset on Individuals' Sleep (Hours) in Pre- vs. Post-Harvest Month

	(1) Sleep β / SE	(2) Sleep β / SE	(3) Sleep β / SE
All			
Sunset Time (Hours)	-0.69***	-0.06	0.04
	(0.15)	(0.23)	(0.26)
Sunset Time*Pre-Harvest	-0.28***	-0.47**	-0.35*
	(0.09)	(0.20)	(0.18)
Mean	8.42	8.42	8.42
Observations	10827	10827	10827
R^2	0.102	0.107	0.117
Adults			
Sunset Time (Hours)	-0.65***	-0.01	0.18
	(0.15)	(0.25)	(0.29)
Sunset Time*Pre-Harvest	-0.25***	-0.44**	-0.39**
	(0.10)	(0.21)	(0.19)
Mean	8.20	8.20	8.20
Observations	8460	8460	8460
R^2	0.139	0.144	0.157
Children			
Sunset Time (Hours)	-0.73***	-0.52	-0.57
	(0.19)	(0.37)	(0.43)
Sunset Time*Pre-Harvest	-0.23*	-0.31	-0.13
	(0.12)	(0.29)	(0.27)
Mean	9.19	9.19	9.19
Observations	2367	2367	2367
R^2	0.131	0.141	0.157
District FE	Yes	Yes	Yes
Season FE	Yes	No	No
Month FE	No	Yes	No
Week-of-Year FE	No	No	Yes

Notes: This table presents the effect of daily sunset time on time allocated to sleep before harvest compared to after harvest on weekdays for crop cultivator households in India. Panel 'All' includes all individuals over the age of 6. Panel 'Adults' includes all individuals over the age of 16. Panel 'Children' includes all individuals between 6 and 16 years of age. Each panel-column combination represents a separate regression estimating Equation (11) on the outcome variable. The interaction term captures the effect of an hour delay in daily sunset time for crop cultivator households in the pre-harvest month compared to the post-harvest month. All regressions include district fixed effects. Column 1 includes season fixed effects, while Column 2 includes month fixed effects and Columns 3 includes week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Chapter 4

Temperature and Human Capital in India

4.1 Introduction

To what extent does the human condition vary with weather? This relationship has been of long-standing interest in the economics literature, and the fact that the earth's climate is warming has renewed interest in the effects of weather on economic outcomes (73; 120; 121; 269). Because human capital is an important driver of economic growth (40; 287; 326), a critical yet understudied question is the impact of temperature on human capital production. This question is of particular interest in developing countries, which will experience disproportionately higher temperatures (190), where predominantly agrarian livelihoods are climate-exposed, and where individuals are unable to consumption smooth over aggregate weather shocks.

We use math and reading test scores for more than 4.5 million children in primary and secondary school to examine how high temperatures affect human capital production in India, where the number of extremely hot days is expected to double by the end of the 21st century. We identify one mechanism of impact through reduced agricultural productivity and estimate impacts of policy interventions designed to offset fluctuations in agricultural income. In developed countries, temperature affects performance primarily through exposure to higher temperatures on the day of the test and the sensitivity of certain parts of the brain to those higher temperatures, effects that can likely be offset by climate-controlled classrooms and test centers (179; 306). However, in poor countries, human capital production may also be affected by agricultural productivity (255), and to the extent that agricultural productivity is temperature sensitive (344; 346), higher temperatures may affect performance through such an agricultural income mechanism.[1]

First, using test scores from an India-wide repeated cross-section between 2006 and 2014, we show that over a longer-run horizon, measured as the number of hot days in the calendar year prior to the year of the test, high temperatures affect both math and reading scores; 10 extra days with average *daily* temperature above 29°C (85°F) relative to 15°C-17°C (59°F-63°F) reduce math and reading test performance by 0.03 and 0.02 standard deviations (SD) respectively. These are economically meaningful effects. Using projections from the Community Climate Systems Model version 4 (CCSM v4), we estimate that by the end of the century higher temperatures would reduce math and reading test

[1]While not the focus of our paper, hot weather can also affect human capital through harmful effects of early childhood exposure to extreme temperature on health (214).

scores by 0.04 and 0.03 standard deviations respectively each year, which, accrued over the course a student's education, is equivalent to a loss of roughly 2 years of schooling.[2] We corroborate these findings using a rich longitudinal study from a large state in Southern India, Andhra Pradesh, where we also find evidence of a day-of-test, physiological effect of heat stress.

Second, we find persuasive evidence that one underlying mechanism for our longer-run results is the harmful effect of higher temperatures on agricultural yields and incomes: (a) high temperatures have large negative effects on both agricultural yields, (b) hot days during the agricultural growing season have large negative effects on test score performance whereas those in the non-growing season have minimal effects, and (c) the effects of high temperatures are concentrated in warmer regions that grow below-median levels of heat-resistant crops. Other channels could, in theory, mediate the relationship between longer-run temperature and test scores, such as heat stress affecting learning in schools, school closures and teacher absenteeism driven by excessive heat, and incidence of diseases that thrive in hot and wet conditions. While we fail to find strong evidence for these mechanisms, we do not rule them out completely.

Third, we examine the effect of a national policy, designed to offset fluctuations in agricultural income, in modulating the effect of temperature on test scores. We consider the world's largest workfare program, the National Rural Employment Guarantee Scheme (NREGA), which guarantees 100 days of paid work each year to every rural household in India. We find that access to

[2]We provide these calculations in Appendix Section C.2. See (265) for a review of educational interventions in developing countries. The underlying assumption here is, *ceteris paribus*, that the only thing that changes is the underlying temperature distribution with no changes to underlying trends in adaptation along policy, technology, or other margins.

NREGA in the previous year attenuates the marginal effect of extra hot days in the calendar year prior to the test, on both math and reading test scores by 38%. We also show that hotter days in the previous year increase participation in NREGA contemporaneously. Our NREGA results not only reinforce the underlying agricultural income mechanism linking hotter days to lower test scores, but also demonstrate the critical role of social protection programs in helping the poor cope with climate stressors.

In investigating how higher temperatures affect performance and human capital, we connect two distinct literatures. The first is the literature that examines the relationship between weather and economic outcomes, within which a small number of new papers have considered the relationship between temperature and human capital (98; 179; 306).[3] These studies have been set in developed countries, limiting them to a singular channel: the physiological effect of day-of-test temperature on math, but not reading performance (179; 306). However, they fail to find evidence for the effects of temperature on test scores over a time horizon longer than the day of the test. (98) does find that longer-run exposure to heat stress during the summer months affects both math and reading scores in South Korea, but the study is ambivalent about the underlying mechanism. In this paper, we provide the first evidence for the day-of-test physiological effects of heat stress, and more importantly, the effects of longer-run temperature on human capital, in a developing country context. Furthermore, in contrast to previous work, we find evidence that one mechanism underlying the effects of longer-run temperature on test scores is agricultural income. Our work highlights the fact that a shared environmental issue—high

[3]A rich literature considers the impacts of higher temperatures on a variety of economic outcomes including output (72; 73; 365), mortality (38; 70; 130), morbidity (419), and conflict (74).

temperatures—may have vastly different mechanisms and impacts depending on the country context, emphasizing the importance of examining environmental issues in developing countries (181).

Second, we contribute to a new but growing literature on the role of public programs in helping households and individuals cope with environmental shocks. Relevant work in this literature includes (126), who explores the role of social safety net transfers in providing insurance to US hurricane victims; (183), who find that a randomized public health intervention (vitamin A supplementation) in Bangladesh protected infants from negative tornado impacts; and, (6), who find that conditional cash transfers in Mexico mitigate the negative impacts of early-life rainfall shocks on child human capital attainment. Our paper is the first to provide evidence on the role of public programs in helping households in poor countries to cope contemporaneously with extreme temperatures. As such, we demonstrate that social protection programs such as NREGA reduce the temperature sensitivity of poor households, providing benefits that have previously received little consideration (204).[4] In doing so, we identify an important policy instrument for adaptation, especially in developing countries where the rural poor are often unable to smooth consumption over district-level aggregate weather shocks.

The rest of the paper is organized as follows. In Section 4.2, we provide a conceptual framework for the varying channels through which temperature could affect human capital production and in Section 4.3 we describe the numerous datasets used in this paper. In Section 4.4 we cover the main empirical specifications and the corresponding results. In Section 4.5.1 we provide

[4] The closest work to us in this regard is (154), who shows that NREGA weakens the relationship between rainfall and conflict.

evidence that the underlying mechanism is agricultural income and in Section 4.5.2 we explore other candidate mechanisms. In Section 4.6 we demonstrate the role of social protection programs for adaptation and in Section 4.7 we provide concluding remarks.

4.2 Background

There are several mechanisms by which high temperatures could affect human capital accumulation. The two foremost mechanisms are an agricultural channel and a physiological channel. We provide more background on each of these channels below.

Agriculture is the primary occupation for a significant proportion of low-income households in developing countries, whether through subsistence agriculture or as hired labor. Agricultural incomes, however, can be low and erratic in the face of adverse weather conditions, as agricultural productivity in low-income countries is sensitive to both rainfall and temperature. Furthermore, markets in these agrarian economies are incomplete or imperfect. Thus, agricultural households in low-income countries are often unable to smooth consumption over states of nature and across time. In such a context, investments in children may be influenced by household consumption needs instead of the rates of return. That is, if households cannot borrow, lend or store, negative income shocks could reduce human capital investment. For instance, (216) argue that time devoted to schooling is influenced by family resources by showing that income fluctuations among households in India lead to variability in school attendance. Similarly, (221) shows that children living in regions that experienced adverse rainfall shocks had lower investments in education and health. Since time and income are important inputs into human capital, increased volatility in agricultural incomes due to weather conditions can have significant implications for children's educational outcomes in developing countries.

India is a hot country and currently experiences close to 50 days with average temperature over 29°C (84°F), compared to seven days over 29°C in the United States. Furthermore, more than 60% of the Indian population lives in rural areas and depends on agriculture for their livelihood. Therefore, if agricultural yields and the demand for agricultural labor is affected by the physical relationship between heat stress and crop growth (344; 346), and if agricultural households are liquidity constrained,[5] higher temperatures could lead to a reduction in children's human capital investment for many households, through reductions in time and resources devoted to schooling or health investments in children (216; 221; 255). Thus, higher than normal temperatures in the previous period can have negative impacts on children's current human capital outcomes through reductions in the previous- and current-period resources available to the household. Conversely, it is possible that higher temperatures during the previous year could affect human capital via a farm labor productivity mechanism. For example, if children perform agricultural labor, their marginal product of on-farm labor will likely be higher during years with fewer hot days. As a result, parents may decide to keep children home from school more during those years. Conversely, during a year with many hot days, it may be more valuable for children to develop their human capital at school. Under this mechanism, higher than normal temperatures in the previous period would have positive impacts on children's current human capital outcomes.[6]

[5] See for example, (70; 101; 113; 122; 125; 315; 333; 335; 406).

[6] (356) find evidence of this effect in India, but looking at low rainfall, rather than hot days.

High temperatures could also affect children's human capital production through a physiological mechanism. Ambient temperature affects brain temperature. The brain's chemistry, electrical properties, and function are all temperature sensitive (66; 116; 200; 341; 423), and both warm environmental temperatures and cognitive demands can elevate brain temperature. There exists a vast body of empirical evidence linking cognitive impairment to high temperatures as a result of heat stress. For instance, military research has shown that soldiers executing complex tasks in hot environments make more errors than soldiers in cooler conditions (155; 161). Further, LED lighting, which emits less heat than conventional bulbs, decreases indoor temperature, and has been shown to raise productivity of workers in garment factories in India, particularly on hot days (5). Exposure to heat has also been shown to diminish attention, memory, information retention and processing, and the performance of psycho-perceptual tasks (208; 412). Note that cold temperatures have also been shown to have an adverse effect on learning and cognitive function (245; 257; 279; 357; 379). However, India experiences few very cold days in a year, and the number of hot days are projected to increase disproportionately in the future. Hence, the focus of this paper is on hot, rather than cold, days.

Exposure to high temperatures can manifest in insults to children's human capital through the physiological mechanism in two ways: i) a hot day could continue to affect future learning if the human body is unable to internally self-regulate to higher ambient temperatures, and ii) repeated exposure to heat stress at school can affect learning repeatedly. (179), (306) and (98) show that day-of-test temperatures affect test scores through a physiological relationship between heat stress and cognition. However, these studies either found no evidence for the effects of longer-run temperature on cognition (179; 306), or are ambivalent about the underlying mechanism (98).

In Section 4.5.1 we present compelling evidence for agricultural income as one mechanism underlying the longer-run temperature-test score relationship. Subsequently, in Section 4.5.2 we examine the influence of the physiological mechanism, and although we fail to find strong evidence for such a mediating channel, we do not rule it out completely. Other mechanisms through which high temperatures might affect children's human capital in India include incidence of diseases that thrive in hot and wet conditions, and school closures or teacher absenteeism driven by excessive heat. We also explore these channels in Section C.3.

4.3 Data

In this section, we describe the data sets that we use to explore the relationship between temperature and test scores. We use multiple data sets on test performance as well as detailed daily gridded weather data that include temperature, rainfall, and humidity. We obtain agricultural data from the International Crops Research Institute for Semi-Arid Tropics (ICRISAT).

4.3.1 Test Scores

We obtain data on cognitive performance from two sources of secondary data: the Annual Status of Education Report (ASER) and the Young Lives Survey (YLS). The ASER provides a repeated cross-section that allows us to generate a pseudo-panel at the district level for all of India, whereas the YLS is an individual panel that provides coverage for the single state of Andhra Pradesh.

Annual Status of Education Report

The Annual Status of Education Report is a survey on educational achievement in primary school children in India and has been conducted by Pratham, an educational non-profit, every year starting in 2005. The sample is a nationally representative repeated cross-section at the district level. The ASER surveyors ask each child aged from 5 to 16, up to four potential questions in math and reading. In each subject, the surveyors begin with the hardest of the four questions. If a child is unable to answer that question, they move on to the next hardest question, and so on and so forth. The questions are asked in the child's native language,

The ASER is a valuable data set for our analysis for multiple reasons. First, ASER provides national coverage and a large sample size; in our study period of 2006 to 2014, ASER conducted more than 4.5 million tests across every rural district in India.[7] Given the considerable spatial variation in weather in India, the national coverage of ASER allows us to study the impacts of temperatures on test scores over a large support. Importantly, it is administered each year on two or three weekends during the period from the end of September to the end of November, limiting considerations of spatially systematic seasonality in data collection. Second, unlike schools-based data, ASER is not administered in schools and therefore covers children both in and out of school. To ensure that children are at home, the test is administered on weekends. This allows us

[7]While the ASER originated in 2005, the 2005 wave is not publicly available.

to measure effects on test performance without confounding selection related to school attendance or access to schools. Note that ASER samples households, not children. All children in the 3-16 age group who are resident in the samples households are included in the survey, while learning assessment are done with all children age 5-16.

The ASER has two limitations. First, its repeated cross-sectional nature doesn't allow us to account for the role of prior human capital accumulation. Second, the ASER test instrument is relatively simple and is designed to capture the left-tail of the distribution, e.g., to test for basic competence.[8] Note that we address these limitations by complementing our ASER analysis with an analysis of the YLS test data (described below), which is a much broader test that effectively captures variation across the ability spectrum (362).

Young Lives Survey

The Young Lives Survey is an international study of childhood poverty coordinated by a team based at the University of Oxford.[9] The YLS study in India collects data from a single state, Andhra Pradesh, which is the fourth-largest state in India by area and had a population of more than 84 million in 2011. In this study, we use YLS data from 2002 to 2011. The study has collected data on two cohorts of children: 1,008 children born between January 1994 and June 1995, and 2,011 children born between January 2001 and June 2002. Data were

[8]However, the left-tail of the distribution or low-performing students are more likely to come from households with marginal livelihoods, especially considering the scope of the ASER data: *rural* districts in India. Thus, the ASER data set is ideal for investigating the hypothesized income channel underlying the temperature-test score relationship.

[9]Young Lives is funded by UK aid from the Department for International Development (DFID). The views expressed here are those of the author(s). They are not necessarily those of Young Lives, the University of Oxford, DFID, or other funders.

collected from children and their families using household visits in 2002, 2006, 2009, and in 2013/14. Extensive test data were collected from children in the sample in all rounds of the survey. The tests differed in terms of which dimension of cognitive achievement they attempted to capture and how closely they related to the formal school curriculum in Andhra Pradesh; often, different tests were administered to children across rounds in order to ensure that they were appropriate for each child's age and current stage of education. In contrast to the ASER tests, the YLS tests are much longer and more comprehensive, with the math questionnaire containing 30 questions and the reading test covering close to 100 questions. Furthermore, YLS has additional information about the socio-economic background of the children's households and health data. We restrict our sampling frame to children who were in enrolled in school (362), and were tested at least thrice in both math and verbal.

4.3.2 Weather Data

In an ideal research setting, we would use observational weather data from ground stations in each location where the ASER and YLS data were collected. However, the spatial and temporal coverage of ground stations in India is poor. In the absence of consistent coverage from ground weather stations, we use temperature, precipitation, and relative humidity reanalysis data from the ERA-Interim archive, which is constructed by researchers at the European Centre for Medium-Term Weather Forecasting. Such reanalysis data has been supported in the literature as generating a consistent best-estimate of weather in a grid-cell and has been used extensively in economics (26; 344). We use the ERA-Interim daily temperature and precipitation data on a 1 x 1 degree latitude-longitude grid, from 1979 to present day. (117) provide more details about the methodology and construction of the ERA-Interim data set. To construct weather variables for each district or village, we construct an inverse-distance weighted average of all the weather grid points within a 100-kilometer range of the district centroid. For each district, we construct the daily average temperature, daily total rainfall, and daily mean relative humidity.[10] Figure 4.1 shows the spatial distribution of temperature in India during the study period and Figure 4.2 shows the distribution of daily temperatures for India and the state of Andhra Pradesh.

4.3.3 Other Data Sources

Agricultural Yields and Rural Wages

We use agricultural data from the Village Dynamics in South Asia Meso data set, which is compiled by researchers at the International Crops Research Institute for the Semi-Arid Tropics (209). The data set provides district-level information from 1979 to 2014 on annual agricultural production, prices, acreage, and yields, by crop. We generate aggregate price-weighted district level measures of total yield in each district for the six major crops (rice, wheat, sugarcane, groundnut, sorghum, and maize), as well as the five major monsoon crops (excludes wheat). ICRISAT also provides data on district-level averages of yearly rural wages.

[10]Because we are using gridded weather data measurement error is likely classical and therefore resulting in attenuation bias. To the extent that such measurement error exists, our reported results constitute a lower bound on the effects of temperature on test scores.

National Rural Employment Guarantee Act

The National Rural Employment Guarantee Act, also known as the Mahatma Gandhi National Rural Employment Guarantee Act, is the largest workfare program in the world. It legally guarantees each rural household up to 100 days of public-sector work each year at the prevailing minimum wage. It was rolled out non-randomly, in three phases, according to a backwardness index developed by the Planning Commission of India (320). The backwardness index was based on three outcomes—agricultural wages, agricultural productivity, and the fraction of low-caste individuals in each district—based on data from the mid-1990's. The first phase began with 200 districts in February 2006; an additional 130 districts received the program in 2007. By April 2008 the scheme was operational in all rural districts in India. Any rural resident who is 18 years or older can apply for work at any time of the year. Men and women are paid equally, though at least one-third of the beneficiaries must be women. Projects under NREGA involve construction of local infrastructure that improves water management through conservation, rain water collection, and irrigation, as well as flood control, drought proofing, rural connectivity, and land development. NREGA wages vary from state to state, but the floor and ceiling wages under the scheme are set by the central government. We obtain data on NREGA participation for the period from 2006 to 2016 from the Management Information Systems (MIS). In particular, we focus on the number of rural households enrolled in NREGA in a particular district in a given year.

4.4 Do Longer-Run Temperatures Affect Test Scores?

To examine the effect of temperature on test scores, we rely primarily on the ASER data set. The ASER data set has the advantage of national coverage, with greater spatial variation in temperature exposure with a repeated yearly cross-section at the district level. To verify the robustness of our results, we also analyze the YLS data set, which provides an individual level panel but with coverage limited to a single state. With each data set we estimate both flexible and parsimonious models.

4.4.1 Empirical Strategy

To understand the relationship between temperature and test scores throughout India, we use the ASER data set. Following (129) and (203), we first estimate a flexible model:

$$Y_{iajqt} = \sum_{k=1}^{10} \gamma_k TMEAN^k_{jq,t-1} + f\left(rain_{jq,t-1}\right) + g\left(humidity_{jq,t-1}\right) + \chi_a + \alpha_j + \mu_t + \epsilon_{ijqt} \tag{4.1}$$

Y_{iajqt} is math or reading test scores for child i, of age a, in district j, in state q, in year t, standardized by year-age. $TMEAN^k_{jq,t-1}$ is the k^{th} of 10 temperature bins in year $t-1$. We estimate separate coefficients γ_k for each of these k bins. The coldest temperature bin is a count of the number of days with average temperature less than 13°C, and the hottest temperature bin is a count of the number of days with average temperature greater than 29°C. We chose these endpoints because 13°C and 29°C are the 10th and 90th percentiles of average daily temperatures across India from 2006 to 2014. The bins in between are evenly spaced two degrees apart. The omitted bin is the 15°C-17°C bin, which we chose to omit because it has the maximum coefficient of all the bins (e.g., it has the most optimal effect on test scores). All other bins are interpreted relative to this bin. For example, γ_{10}, the coefficient on the hottest bin, is the marginal effect on test scores of an extra day with average temperature greater than 29°C relative to a day with average temperature between 15°C and 17°C.

For rainfall, we control for dummy variables that represent whether total annual rainfall for a certain district in a certain year was in the top, or bottom, tercile, relative to the long-run historical distribution of rainfall in that district.[11] For humidity, we control for dummy variables for whether average annual humidity for a certain district in a certain year was in the top, or bottom, tercile. We control for age fixed effects (χ_i), district fixed effects (α_j) and year fixed effects (μ_t). We cluster standard errors at the district level to account for serial correlation within a district over time. Each coefficient γ_k is identified under the assumption that, after controlling for rainfall and humidity, changes in the number of hot days are exogenous to district-specific unobservable characteristics that vary over time. The assumption is plausible given the randomness of weather fluctuations and the inability of rural households in India to predict such fluctuations. In estimating this flexible approach we follow prior work in climate economics and avoid imposing restrictive assumptions on the functional relationship between temperature and test scores (203). We also estimate a parsimonious version of Equation (4.1) with an upper threshold of 21°C and a lower threshold of 15°C. Our choice of 15°C and 21°C for the parsimonious

[11]Our results are robust to alternative specifications of rainfall, including linear and quadratic terms for total annual rainfall.

model is based on the kink points that were revealed by our estimation of the nonparametric analysis (Equation 4.1).

$$
\begin{aligned}
Y_{ijaqt} = &\gamma_1 TMEAN(> 21°C)_{jq,t-1} + \gamma_2 TMEAN(< 15°C)_{jq,t-1} \\
&f\left(rain_{jq,t-1}\right) + g\left(humidity_{jq,t-1}\right) + \chi_a + \alpha_j + \mu_t + \epsilon_{ijqt}
\end{aligned}
\tag{4.2}
$$

An important limitation of the ASER data is that it does not provide the exact date of the test. Therefore, we can't control for day-of-test temperature. However, the omission of temperature on the day of the test would only confound our estimates if the day-of-test temperature is correlated with more hot days in the previous year. We believe that such a systematic correlation is unlikely because the day-of-test temperature is plausibly random.[12]

4.4.2 Results

We estimate Equation (4.1) and find that, relative to a day with average daily temperature between 15°C and 17°C, one extra day in the previous year with average daily temperature above 29°C reduces math and reading performance by 0.003 and 0.002 SD in the current year, respectively (Table 4.1). Using our binned approach, we find that test performance decreases for temperatures above 17°C. The results are similar to those estimated with our parsimonious approach: one extra day above 21°C reduces math and reading performances by 0.002 and 0.001 SD, respectively (Table 4.2).[13]

[12] In fact, we test this assumption explicitly using the YLS data where we have information on the day of the test.

[13] In addition to the significant negative effects of high temperatures, there are two other features to note about Table 4.1: first, there are also negative impacts of very low temperatures and,

In addition to our analysis of standardized test scores, we also estimate the effects of previous year temperature using raw scores (Figure C.2). We find that a 10-day increase in the number of hot days above 29°C in the previous year decreases math scores by 0.03 points and reading scores by 0.02 points.[14] Both point estimates are statistically significant at the 5% level. Furthermore, to understand how higher temperatures impacted specific skills, we present effects on competencies covered on both math and reading tests. The effects of heat are driven by the harder questions on both math and reading tests. We find large negative effects on paragraph- and story-reading skills, but statistically insignificant effects on word- or letter-reading skills (Figure C.3). Ten extra days in the previous year with average daily temperature above 29°C (84°F) relative to 15°C-17°C (59°F-63°F) reduce story-reading ability by almost 1 percentage point. In 2006, almost 45% children in the ASER data set could read a story, so 1 percentage point decrease translates into a reduction of 2% in story reading skills. Similarly, we find negative effects on division and subtraction skills, but statistically insignificant effects on single- or double-digit number recognition (Figure C.4). Ten extra days in the previous year with average daily temperature above 29°C (84°F) relative to 15°C-17°C (59°F-63°F) reduce division-solving ability by more than 1 percentage point, or 3%.

second, the gradient of the temperature impacts is relatively flat. The low temperature impacts are not the focus of our study, because there are fewer days in these bins and, furthermore, the number of days in these bins will decrease as climate change accelerates. However, as noted in Section 4.5.2, these cold-temperature impacts may be due to a physiological channel. Second, the flat gradient of the graph stands in contrast to other work on temperature impacts that often finds sharp threshold effects, such as (346). However, as explored further in Section 4.5, this flat gradient may arise because the annual specification captures the combined effects of many channels (e.g. agricultural, physiological, and other), across many parts of the year (e.g. growing season versus non-growing season), which may vary in magnitudes.

[14] The average scores for both math and reading tests are approximately 2.5 points out of the maximum possible score of 4.

Robustness Checks: We demonstrate that our results are insensitive to numerous robustness checks, supporting the validity of our baseline model. First, we find no effect of hotter days in the current year or the next year on performance in the current year, and including these does not appreciably change our primary coefficient of interest (Table 4.2). Second, our point estimates are quantitatively similar for the limited sample of "on-track" students who are in the correct school-grade-for-age (Table C.1). Third, the addition of lags does not affect our point estimates (Table C.2). Fourth, our results remain unchanged with the inclusion of state-specific linear and quadratic trends (Table C.3). Fifth, our results remain unchanged with the inclusion of state-by-year fixed effects, which control for all time-varying unobservables at the state-level that may be correlated with children's test scores (Table C.4). Sixth, our results remain largely unchanged when we use nearest weather grid points or daily maximum temperature (Table C.5). Finally, we also control for a proxy of the same-day temperature—the number of hot days during the weekends of the testing month—and find that controlling for this does not change the coefficients appreciably (Table C.6).[15]

4.4.3 Individual Panel Analysis

Next, we use a longitudinal panel data set—the YLS—in which we have information on the exact date of the test, allowing us to control for temperature on the day of the test, as well as time-invariant child level attributes (e.g., ability), and estimate the effect of hot days between successive tests (covering at least one full agricultural cycle) on test scores.

[15]Recall that we have to use such a proxy since the exact day of the ASER test is unavailable. We do, however, know that these tests take place during the weekends.

Empirical Strategy We first estimate the following flexible model of the effects of temperature on test scores:

$$
\begin{aligned}
Y_{ijdmt} = {} & \gamma_2 T(23^\circ C - 25^\circ C)_{j,t-1} + \gamma_3 T(25^\circ C - 27^\circ C)_{j,t-1} + \gamma_4 T(> 27^\circ C)_{j,t-1} \\
& + \beta_2(23^\circ C - 25^\circ C)_{jdmt} + \beta_3(25^\circ C - 27^\circ C)_{jdmt} + \beta_4(> 27^\circ C)_{jdmt} \\
& + f\left(rain_{j,t-1}\right) + rain_{jdmt} + \alpha_i + \mu_{1d} + \mu_{2m} + \mu_{3t} + \epsilon_{ijdmt} \qquad (4.3)
\end{aligned}
$$

Y_{ijdmt} is the math or reading test score of child i in district j on day-of-week d in month-of-year m in survey-round t, standardized by year-age. Our coefficients of interest are $T(\cdot)$, counts of the number of the days since the previous test with average daily temperature within the specified range. For example, $T(23^\circ C - 25^\circ C)$ is the number of days since the last test with average daily temperature between 23°C and 25°C. We control for cumulative rainfall, and include fixed effects for child (α_i), day-of-week (μ_{1d}), month-of-year (μ_{2m}), and survey-round (μ_{3t}). Inclusion of child fixed effects controls for unobservable child level attributes that do not vary over time (e.g., ability). Furthermore, we control for day-of-test temperature by including dummies indicating temperature was between 23°C and 25°C, 25°C and 27°C, or above 27°C, respectively. This also allows us to capture the effects of temperature on the day of the test. For instance, β_4 is the marginal effect of the average day-of-test temperature being above 23°C relative to a day with average temperature below 23°C. $rain_{jdmt}$ controls for rainfall on the day of the test.

Since the YLS data covers a single state (Andhra Pradesh), the temperature distribution is narrower than in the other national data sets that we use. Furthermore, since the number of days in a year is fixed at 365, we normalize the coefficient on the "optimal" temperature bin, in this case $T(< 23^\circ C_{jt})$, to 0, making it the reference bin. Thus γ_4 is the marginal effect of an extra day since the last test with average temperature above 27°C relative to a day with average temperature below 23°C. Our four temperature bins have, on average, an equal density with 23°C, 25°C, and 27°C representing the first, second and third quartiles of the temperature distribution in Andhra Pradesh during our study period. We cluster standard errors at the district-week level to allow for arbitrary correlation in test scores in a district in a given testing week and for conservative inference when multiple children are assigned the same temperature observation. Each γ_i is identified under the assumption that the number of hot days experienced by a child in a given bin between successive tests is exogenous to child-specific unobservable characteristics that vary over time. Importantly, by tracking the same children over time, we are able to account for prior human-capital production and provide causal estimates of the effects of the daily temperature distribution between successive tests on changes in student test performance.

We also estimate a second parsimonious approach with a single temperature cutoff instead of flexible temperature bins:

$$\begin{aligned} Y_{ijdmt} &= \gamma T(>23^{\circ}C)_{j,t-1} + \beta(>23^{\circ}C)_{jdmt} + f\left(rain_{j,t-1}\right) + rain_{jdmt} \\ &\quad + \alpha_i + \mu_{1d} + \mu_{2m} + \mu_{3t} + \epsilon_{ijdmt} \end{aligned} \tag{4.4}$$

The notation is the same as in Equation (4.3), with the key difference that $T(>23^{\circ}C)_{jt}$ is a count of the number of days above 23°C experienced by a student district j between successive tests. Following the common practice in the literature on climate economics, we chose the threshold of 23°C because our estimation of the nonparametric specification (Equation 4.3) revealed a kink at that level (203).

Results: We find qualitatively similar (though quantitatively larger) effects when we estimate Equations (4.3) and (4.4) using the YLS individual panel data set. We find that 10 extra days between successive tests above 27°C relative to below 23°C reduce math and reading test scores by 0.07 and 0.10 standard deviations, respectively (Table 4.3).[16][17]

Furthermore, consistent with the neuroscience literature and recent work in economics on the impacts of temperature on cognitive performance, we find strong evidence for the presence of a physiological channel connecting temperatures to test scores in the short run (66; 200; 341). Specifically, we find that a 1°C increase in average day-of-test temperature above 23°C reduces within-cohort math test performance by 0.17 standard deviations, but find no discernible or meaningful relationship between higher temperatures and reading comprehension. Different portions of the brain perform different cognitive functions. For instance, the pre-frontal cortex, which is responsible for providing the "working memory" needed for performing mathematical problems, is more temperature sensitive than the portions of the brain responsible for reading functions (200). These day-of-test estimates are similar with those in prior work in developed countries (98; 179; 306). Crucially for our analysis, controlling for day-of-test temperature does not affect the relationship between longer-run temperature and test scores (Table C.9).

Recall that the ASER test instrument primarily captures variation in the left-tail of the ability spectrum, whereas YLS is a more comprehensive test that captures variation over the entire distribution of ability. The fact that our results are

[16]While our YLS analysis includes only the younger sample to maintain comparability with the ASER results, the results are similar to when we consider the combined sample as well (Table C.7).

[17]We also cluster-bootstrap our standard errors at the district level (7 clusters) following (79). Our estimates remain precisely estimated (Table C.8).

consistent across the two data sets indicates that temperature shocks over the previous year have impacts on both low-performing students and students on other levels of the ability spectrum. From a policy point of view, we care about both groups of students: low-performing students may be coming from particularly disadvantaged households or vulnerable livelihoods; but conversely to understand economy-wide impacts, it is important to understand impacts that span the entire ability distribution.

4.5 Mechanisms

In this section we examine two primary mechanisms that may mediate the longer-run temperature-test score relationship: i) agricultural income and ii) direct physiological impacts on learning. Other plausible mechanisms such as the incidence of diseases that thrive in hot and wet conditions and school closures or teacher absenteeism driven by excessive heat are explored in Section D.1.

4.5.1 Is Agriculture a Mechanism Underlying the Relationship Between Longer-Run Temperatures and Test Scores?

If agricultural yields and the demand for agricultural labor are affected by the physical relationship between heat stress and crop growth, and if agricultural households are liquidity constrained, then higher temperatures could lead to a reduction in children's human capital investment. For instance, we find that previous year temperature reduces current year school attendance (Table C.10) and children's body mass index (Table C.11), which suggests decreases in time and resources devoted to schooling (216) and health investments (221) in children. Thus, if higher temperatures have large, negative effects on agricultural income in the previous year, it is possible that these effects have consequences for children's human capital production in the future. We find strong evidence in support of such a pecuniary mechanism underscoring the effect of temperature on test scores. First, we provide evidence that agricultural yields respond negatively to higher temperatures. Next, we use the ASER data to provide two distinct tests to support the agricultural income hypothesis: (a) comparing effects of hot days across the growing and non-growing seasons of the agricultural calendar, and (b) comparing effects of heat on test scores across the geographic dispersion of heat-resistant crops.

Temperature and Agricultural Yields

To demonstrate that temperature affects human capital production by affecting the livelihoods of the rural poor, we first demonstrate that temperature affects agricultural yields. We find that agricultural yields, like test scores, are highly responsive to higher temperatures in the growing season, with comparatively modest effects of non-growing season temperatures. We use two different price-weighted agricultural yield indices: (a) the six major crops (rice, wheat, sugarcane, groundnut, sorghum, and maize), and (b) the five major monsoon crops (excludes wheat).

Growing Season versus Non-Growing Season

To further demonstrate evidence of an agricultural mechanism, we disaggregate our results by the growing season versus the non-growing season. India's main agricultural season (*kharif*) runs from June through November and the secondary growing season (*rabi*) runs October through February. We know that the ASER test is conducted in a given district on a single weekend between the end of September and the end of November. If hot days affect test scores by affecting household income that relies on agricultural output, these effects must be predominantly driven by growing season temperatures in the previous year. Thus, we subdivide each temperature bin in Equation (4.1) into days in that bin in the growing season and days in that bin in the non-growing season. We define the growing season as June through December and the non-growing season as March through May, broadly following the approach in (70). We exclude January and February from the growing season because very few hot days occur during these months. We focus on the growing season of the previous year (rather than the current year), because the previous year's output has been fully harvested, whereas the current year's harvest may be still in progress, at the time of the ASER test.

We find that the effect of temperature on test scores is primarily driven through higher temperatures in the previous years' agricultural growing seasons: an extra hot day above 29°C in the growing season has an order of magnitude larger effect on test scores than a corresponding extra hot day above 29°C in the non-growing season. Specifically, an extra 10 days above 29°C in the growing season reduce math scores by 0.1 standard deviations and reading scores by 0.06 standard deviations, compared to negligible effects in the non-growing season (Figure 4.4). These are large effects: 10 extra hot days in the previous year growing season could effectively wipe out gains made from a median educational intervention (265). Furthermore, the difference between the effect of an extra hot day above 29°C in the growing season versus the non-growing season is statistically different at the 1% level. The differences between the effects of temperature on test scores across growing versus non-growing seasons increase with higher temperatures for both math and reading scores.

Additionally, we test the impact of temperature across the growing and non-growing seasons on agricultural yields of the six major crops as well as the five major monsoon crops. Using district level yields data, we find that an extra day above 29°C in the growing season reduces yields by three times more than the same type of day in the non-growing season. In absolute terms, the magnitude is large; an extra day above 29°C in the growing season relative to a day between 15°C and 17°C reduces yields by 1% (Figure 4.4), with no effect of temperature on yields in the non-growing season. Our estimates are comparable to those found elsewhere in the literature (70; 83; 376). Consistent with our finding of extremely cold days reducing performance, cold days also reduce agricultural yields, though to a lesser extent than hot days.[18][19] The large impact of temperature on yields in the growing season but not in the non-growing season is consistent with a model in which temperature affects test scores through declines in agricultural income.

Our test score results are robust to several specification variation. Our base-

[18]In addition to analyzing aggregate, price-weighted yields, we have estimated temperature bin regressions for the raw yields (tons/hectare) of the six major crops. The results demonstrate that high temperatures negatively affect raw yields (Figure C.8).

[19]We also find that rural wages respond linearly to higher temperatures. An extra day above 29°C (relative to a day between 15°C and 17°C) decreases rural wages by 0.4% (Figure C.7). However, because our wage data is annual, we are not able to disaggregate this result by the growing versus the non-growing season.

line specification uses dry bulb temperatures, rather than wet bulb globe temperature (WBGT), because we believe that agricultural income is the primary channel that is driving the temperature-test score relationship. However, our results are qualitatively and quantitatively similar to using WBGT instead of dry air temperatures (Figure C.5). Separately, our baseline specifications are clustered at the district level. However, to address concerns over spatial correlation, we also run a specification with standard errors clustered at the state-level. The coefficients for previous year's growing season temperature bins remain precisely estimated (Figure C.6). Finally, we also show as a falsification test that future temperatures don't affect prior agricultural yields (Table C.13).

Heat-Resistant Crops

To further explore the impact of temperature on agricultural yields and test scores, we analyze the role of heat-resistant crops. Following (207), we separate crops into C4 crops and C3 crops. C4 crops extract carbon from carbon dioxide more efficiently than C3 crops, and are more resistant to high temperatures. In our data, the C4 crops are maize, sorghum, pearl millet, sugar cane, finger millet, and fodder, and all remaining crops are C3. For each district-year, we calculate the fraction of cultivated area that is planted with C4 crops, and then we calculate a long-run average of this value. Then we label a district to be a heat-resistant crop district if its long-run average proportion of C4 crops is above the median, which is 23%. Figure C.9 shows the geographic distribution of the take-up of heat-resistant crops.

We find that the effects of temperature on test scores are pronounced in districts where the dominant crops are not heat-resistant, with no economically meaningful effects of temperature on test scores in districts that grow heat-resistant crops. Since we are interested in the interaction term on heat-resistant crops and temperature, we estimate the parsimonious Equation (4.2) to preserve power. We find that growing heat-resistant crops erases most of the effect of higher temperatures on test scores. An extra 10 hot days above 21°C in districts that grow below-median levels of heat-resistant crops lower math scores by 0.022 standard deviations, compared with a near-null effect in districts that grow above-median levels of heat-resistant crops (Table 4.4).

However, the decision to plant heat-resistant crops is endogenous to, amongst other factors, long-term average temperature, or the "climate normal." Therefore, the decision to grow heat-resistant crops could be a proxy for underlying economic conditions that reflect adaptation to long-term average temperatures along agricultural (e.g., heat-resistant crops) and non-agricultural (e.g., fans) margins. To investigate the differences in the effects of temperature on test scores across different long-term historical climates, we break down the relationship between temperature and test scores based on long-term average temperature deciles. We find that districts with higher historical average temperatures plant a larger fraction of their total cultivated area with heat-resistant crops (Figure 4.6(a)). In the lower and middle deciles, there is very little take-up of heat-resistant crops but in districts with the highest long-term average temperatures, more than 30% of the total cultivated area is covered by heat-resistant crops. Furthermore, the relationship between days with temperature above 29°C and test scores largely follows the take-up of heat-resistant crops; the effects are present only in the middle climate deciles, where there are enough hot days to find a discernible effect but the take-up of heat-resistant crops remains low, for both math (Figure 4.6(b)) and reading scores (Figure 4.6(c)). In the hottest climate deciles, as expected, there is little effect of hot days in the previous year on test scores with high prevalence of heat-resistant crops. These results are consistent with earlier work that has found crop yields in hot regions are less sensitive to higher temperatures, due to agricultural adaptation (376). As an important robustness check, we show that future temperature shocks are not correlated with baseline levels of heat resistant crop adoption (Table C.14).

4.5.2 Can the Physiological Effects of Heat Stress Explain the Relationship Between Longer-Run Temperatures and Test Scores?

In this section, we consider human physiology as a potential underlying mechanism behind the longer-run temperature-test score relationship. Exposure to high temperatures harm children's human capital through the physiological mechanism in two ways: (i) a hot day could continue to affect future learning if the human body is unable to internally self-regulate to higher ambient temperatures, and (ii) repeated exposure to heat stress at school could affect learning repeatedly.[20]

[20]Temperature on day-of-test can affect performance on high-stakes exams and translate into lower human capital production due to the structure of the education system, typically in the form of arbitrary cutoffs for passing or placing into high-achievement programs (306). In our study, however, we evaluate the effects of temperature on low-stakes cognitive tests and abstract away from this pathway.

Persistent Effects of a Hot Day

First, we test whether high temperatures can have persistent impacts: a hot day today could continue to affect performance in the future if the human body is unable to internally self-regulate to higher ambient temperatures. We examine this hypothesis by estimating the lagged effects of short-run temperature using the YLS data set. We find no evidence for the persistence of the effects of short-run temperature on test scores: over the four days prior to the test, heat stress has no effect on test performance (Figure C.10). This pattern largely holds for at least up to four weeks of leads and lags (Figure C.11). The large day-of-test effect and the null week-of-test effect are consistent with a model of internal self-regulation in which the human body self-regulates higher temperatures, making the direct effects of temperature on cognitive performance temporary (380).

Repeated Exposure to Heat Stress

Yet, if children are repeatedly exposed to heat stress at school or on the field, then the cumulative effect of that heat stress can still affect performance as a result of impaired learning. Thus the effect of hot days in the previous year on performance in the current year could also be the cumulative physiological effect of heat stress on learning. To rule out this explanation, we first show that only hot days in the previous calendar year affect performance in the current year, with hot days in the current year having no effect on test scores (Table 4.2). If the physiological mechanism were driving the relationship between annual (or longer-run) temperature and test scores, we would see the effects on performance of hot days in both the current year and the previous year. As explained in Figure 4.3, only hot days in the previous calendar year should affect test scores in the current year through the agricultural income channel.

Second, the physiological channel, unlike the agricultural income channel, should not be contingent on the agricultural calendar. We see strong effects of hot days in the previous year's growing season on test score performance but no effect of hot days in the non-growing season (Figure 4.4). To rule out concerns of overlapping agricultural and schooling calendars, we further split the growing season by months when the school is in session and when students are on break.[21] Our hypothesis is that the physiological effects of heat on learning should be limited to hot days in the school year, whereas the agricultural income mechanism should be in effect during both school and non-school months in the growing season. Consistent with an agricultural income mechanism, we find that hot days in school and non-school months have similar effects on performance (Figure C.12), suggesting that it is unlikely that the relationship between higher temperatures in the prior year and test scores is driven by reduced learning due to heat stress in the classroom.

The combination of large effects of heat in the growing season, paired with the negligible effects of heat during the non-growing season, could also be explained by heat exposure of agricultural workers from working in the field. If these workers are the same children being tested, then the growing season heat effects could be physiological effects on the human body, rather than those driven through an agricultural income mechanism. However, as mentioned earlier, heat stress during the concurrent year as the test has no effect on test scores (Table 4.2). India's main agricultural season lasts from June through November.

[21]Within the growing season that lasts from June through December, June and December typically have summer and winter holidays, with school in session more or less continuously from July through November.

Since ASER tests are conducted from late September to late November, physiological exposure to heat, for children contributing labor to agriculture, would have transpired by the time of the test. Thus, we would expect to see effects of heat exposure in the concurrent year.

Finally, another test for the physiological versus agricultural income channel is to draw a distinction between math and reading scores. Prior studies in both economics and neuroscience posit that the physiological effects of heat are experienced primarily in the part of the brain responsible for mathematical function (179; 200; 306). The effects of short-run (day-of-test) temperature, for example, are seen on math performance but not on reading performance. Our estimates for day-of-test temperatures are consistent with such a hypothesis. However, effects of longer-run (previous calendar year) temperature are observed in both math and reading scores. Furthermore, the magnitude of the effect on both math and reading performance is similar. Together, these results suggest that the longer-run temperature-test score relationship for high temperatures is not driven solely by a physiological mechanism.[22]

[22] In fact, the existence of significant negative effects of cold days may indicate that a physiological mechanism does exist. Our baseline specification finds statistically significant negative impacts from low temperatures in the previous year on current-year test scores. However, our growing vs. non-growing season estimates fail to find strong evidence for existence of an agricultural mechanism for cold days. Thus, it is plausible that cold stress affects learning due to physiological channels (245; 257; 279; 357; 379). Importantly, agricultural income and physiology are not mutually exclusive mechanisms.

4.6 Can Social Protection Programs Mitigate the Relationship Between Longer-Run Temperatures and Test Scores?

If income is indeed one mechanism of impact, can social protection programs play a role in shielding the poor from higher temperatures and facilitating adaptation to climate change? To investigate this question, we consider the largest workfare program in the world—the National Rural Employment Guarantee Act of 2005—which guarantees every person in rural India 100 days of paid employment on rural infrastructure projects, making NREGA a self-targeting conditional cash transfer program that has an income-stabilizing effect in the face of low and erratic agricultural incomes.

4.6.1 Empirical Strategy

If high temperatures reduce crop yields and the demand for agricultural labor in the previous year, it is plausible that rural households use NREGA in the previous year to help smooth consumption, and compensate (at least partially) for heat induced agricultural income losses. Thus, hotter days in the previous year might increase NREGA take-up in that year, attenuating the relationship between previous year temperature and current year test scores.[23] We exploit the

[23]NREGA has been shown to have impacts on a multitude of economic and social outcomes, as reviewed in (374). Outcomes affected include the demand for labor-intensive technologies (53) and agricultural yields, as laborers may switch from agricultural to NREGA participation (377). We abstract away from these details and focus on the net effect of NREGA on the temperature-test score relationship.

staggered district-level roll-out of NREGA and test this hypothesis in an event study framework since the variation in treatment timing could result in biased difference-in-difference estimates (177). To do so, we estimate the marginal effect of an extra hot day above 29°C (relative to between 15°C and 17°C) for the same district before and after the introduction of NREGA. We estimate the following equation:

$$
\begin{aligned}
Y_{iajqt} = & \sum_{k=1}^{10} \gamma_k TMEAN^k_{jq,t-1} + \sum_{\tau=-3,\tau\neq-1}^{\tau=2} \theta_\tau NREGA(t - T^*_j = \tau)_{jq,t-\tau} * TMEAN^{10}_{jq,t-1} \\
& + \sum_{\tau=-3,\tau\neq-1}^{\tau=2} \beta_\tau NREGA(t - T^*_j = \tau)_{jq,t-\tau} + \chi_a \\
& + f(rain_{jq,t-1}) + g(humidity_{jq,t-1}) + \alpha_j + \mu_t + \epsilon_{iajqt} \qquad (4.5)
\end{aligned}
$$

The equation is identical to Equation (4.1) with an additional term, $NREGA(t - T^*_j = \tau)_{jq,t-\tau} * TMEAN^{10}_{jq,t-1}$, which captures the interaction of the number of days in the hottest temperature bin in the previous year with NREGA event time dummies that take values 0 or 1. Specifically, we estimate separate coefficients on the hottest temperature bin for the periods before and after the introduction of NREGA in district j in state q. For instance, event time $T = 0$ takes the value 1 if NREGA was available in any district j in the previous year, 0 otherwise. So, if a district j got NREGA in 2009, $NREGA : T = 0 * Days > 29°C$ captures the interaction of number of days in the previous year where the temperature is over 29°C in 2009 with the dummy variable $T = 0$, to estimate the protective effects of NREGA on children's test scores in 2010. Similarly, the interaction of $T = 1$ with number of days in the previous year where the temperature is over 29°C would capture the compensatory effects of NREGA one year after it was made available to a district j in the previous year. The omitted event time $T = -1$ is the year before the previous year NREGA is introduced in a district, and we interpret the coefficient of interest θ_τ relative to that period. In our baseline specification, we include district (α_j) and year (μ_t) fixed effects. We also control for age-for-grade status considering the level effects of NREGA on grade progression (355). Our specification compares the effect of a hot day on test scores before and after a district received NREGA in the previous year, relative to the effect of that hot day in other districts that didn't receive NREGA in that same year. NREGA was introduced in 2006 and, because all districts had received NREGA by 2008, we restrict the ASER sample to include only survey-rounds between 2006 and 2009. Finally, to address any potential incidental correlation between NREGA and weather shocks, we explicitly test whether future weather shocks predict the rollout of NREGA. In Table C.15 we show that NREGA rollout is not predicted by future temperature shocks.

4.6.2 Results

The main coefficient of interest is the interaction between NREGA event time dummy variables and the number of days above 29°C in the previous year. Consistent with an income mechanism, we find that NREGA attenuates the effect of an extra hot day above 29°C in the prior calendar year on math and reading scores by more than 50% (Table 4.5).[24] Figure 4.6 presents the event study graphically and shows that the introduction of NREGA attenuates the effect of those extra 10 hot days above 29°C on test scores by 0.01 standard deviations on both

[24] We show that prior to NREGA roll-out in a district, an extra 10 days above 29°C (relative to between 15°C and 17°C) reduce math and reading scores by 0.02 and 0.01 standard deviations, respectively, although because we use only data from 2006 to 2009 we are relatively underpowered.

math and reading.[25] We note that the effects of NREGA represent intent-to-treat (ITT) estimates, since not all households in a district will respond by taking up NREGA. We also employ a triple-differences design (comparing the effects of a hot versus a cold day in districts with and without NREGA, before and after they receive NREGA) to estimate the effect of NREGA on the marginal effect of an extra hot day in the previous calendar year and find comparable estimates (Table C.16). Our event study results are robust to a parsimonious model similar to Equation (4.2), with an upper threshold of 21°C and a lower threshold of 15°C (Table 4.6). Our coefficient of interest is the interaction of NREGA roll-out with number of days above 21°C.

Since workfare requires individuals to sign up for work, it would be reasonable to expect NREGA take-up to respond contemporaneously to higher temperatures to offset declines in agricultural incomes. Indeed, we find that NREGA take-up responds to higher temperatures. We obtain annual NREGA district level take-up and expenditure data from 2006 to 2016 and show that hotter days in the current year drive NREGA take-up and expenditures (Figure 4.7). Specifically, an extra hot day with average temperature above 29°C in a district (relative to a day between 15°C and 17°C) increases NREGA take-up by nearly 1.3%. For the same extra hot day in a year, 3.4% more households are likely to use all 100 days of eligibility in the program. For each extra day above 29°C, district NREGA expenditure increases by 2% on labor and nearly 3% on materials. These results suggest that households use NREGA to stabilize damage to agricultural income in hotter years.

The remarkable effect of NREGA in attenuating the relationship between

[25]We find that NREGA exposure has a negative level effect on math and reading scores, and this effect is statistically significant. These are the opportunity cost effects shown in (355).

temperature and test scores is of considerable importance. The result reinforces the underlying income mechanism linking higher temperatures to lower test score performance. Not only do higher temperatures lower test performance by adversely affecting household agricultural income, but income-stabilizing social protection programs can attenuate the negative effects of higher temperatures. The implication is that in poor countries, where large parts of the population are dependent on agriculture, social protection programs can play a central role in shielding the poor from weather and facilitating adaptation to climate change.[26]

4.7 Conclusion

As weather, in the age of climate change, becomes more pronounced, it is likely to dramatically impact the poor by limiting pathways out of poverty that depend on human capital production. We find that temperature in the calendar year prior to the test, or "longer-run" temperature affects human capital production. Furthermore, we show that agricultural income is likely one mechanism driving this relationship. Importantly, these effects are separate from the physiological impacts of day-of-test "short-run" temperature on test performance documented in the literature this far. The separation of the pathways through which temperature affects human capital over different time horizons has important implications for both climate change research and policy.

[26]These types of programs act as a powerful potential "public" adaptation to climate change, which may mitigate some of the most harmful damages from climate change. Importantly, they complement to private adaptations that households can undertake in response to heat, such as crop choice, irrigation, livelihood adjustments and asset purchases, such as fans. Due to the nature of our data, private adaptations fall outside of the scope of our work.

First, the different structural relationships connecting short- and longer-run temperature to economic outcomes highlights the limitations of existing approaches in quantifying ex-post adaptation by comparing the effects of short- and longer-run temperatures (72; 120). This is especially likely to be the case when considering low- and middle-income countries, where the majority of the world's population lives, and where the propagation of defensive investments (e.g., air conditioners) is limited and livelihoods remain climate-exposed. The existence of multiple structural relationships implies that modeling and projecting the impact of climate change in poor countries will require not only understanding how these existing relationships will change over time through adaptation, but also how new structural relationships between temperature and economic outcomes will emerge over the next century.

Second, the presence of multiple pathways linking heat stress and a single economic outcome suggests adaptation to higher temperatures will be required along multiple margins. Effects of short-run temperature, driven by physiology, can likely be corrected through defensive investments such as air conditioners, or by changing the test calendar. For instance, India's main board for primary and secondary education has decided to move the important school-leaving exams that are often the sole criterion in college admissions from March and April, when the average temperatures in India are 22°C and 26°C respectively, to February, when average temperatures are 17°C (176). While this change is not being made explicitly as a response to heat stress, it provides an opportunity to understand how adjustments to the testing calendar can alter the effects of short-run temperature.

By contrast, the effects of longer-run temperature are driven by damage to livelihoods that, in agrarian poor settings, are vulnerable to weather. Importantly, these effects of longer-run temperature may reduce human capital production by adversely affecting agricultural income, and therefore may require social protection programs that can protect the livelihoods of the poor from weather and climate. While there is considerable work on the benefits of conditional cash transfers and similar social protection programs, we know relatively little about the role of such programs in combating vulnerability. If the susceptibility of cognitive performance (or another measure of productivity) to temperature can be characterized as vulnerability, social protection programs can have not only direct effects, but also indirect benefits in reducing vulnerability. Consequently, governments and policy makers should expect the dependence on their social protection programs to increase in the face of climate change. Developing countries will have to carefully allocate scarce resources between productive capital and adaptive capital (272), and will have to make difficult decisions about which margins of climate change damages to adapt to. Given the central role of human capital production as a pathway out of poverty in poor countries (39), climate change will not only affect the livelihoods of the rural poor but also, absent social protection programs, likely perpetuate persistent poverty.

4.8 Tables and Figures

4.8.1 Figures

Figure 4.1: Average Annual Temperature in India at the District Level

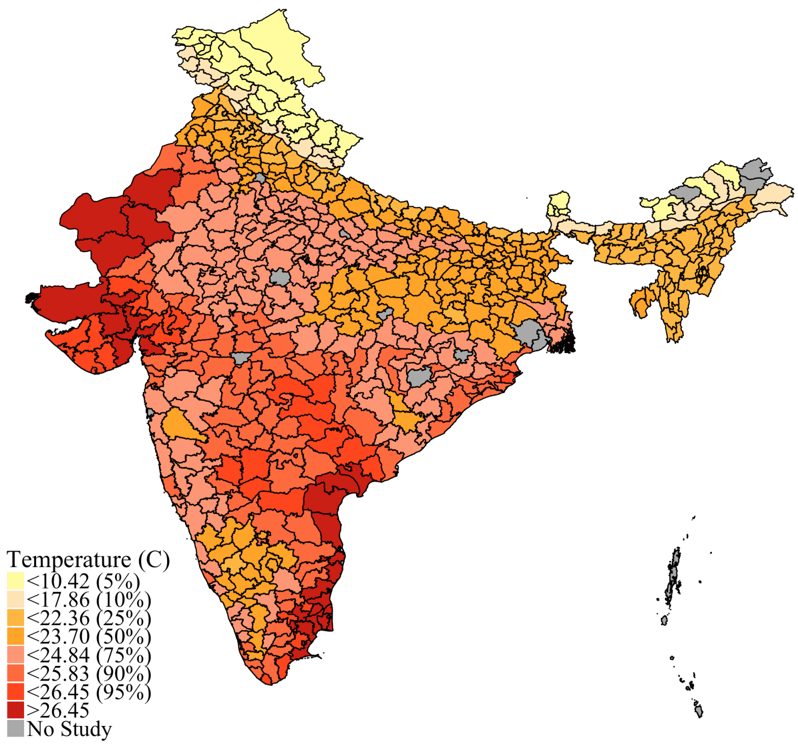


Figure 4.2: Distribution of Daily Average Temperatures for India and Andhra Pradesh

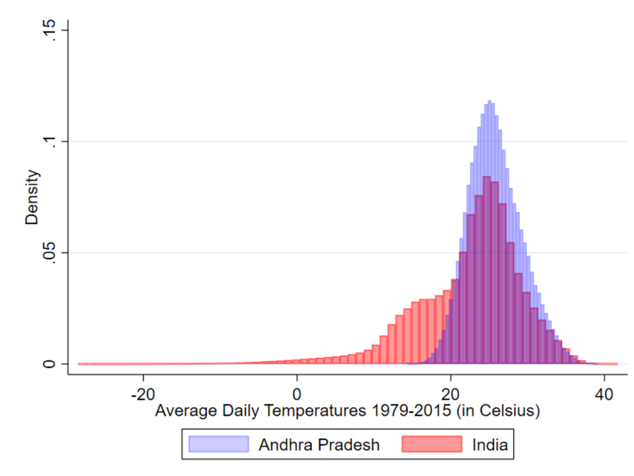
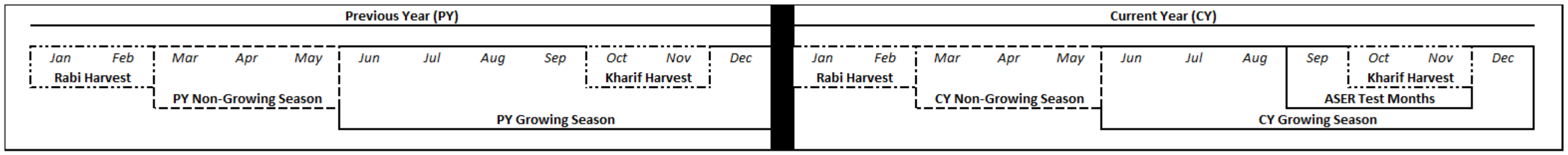
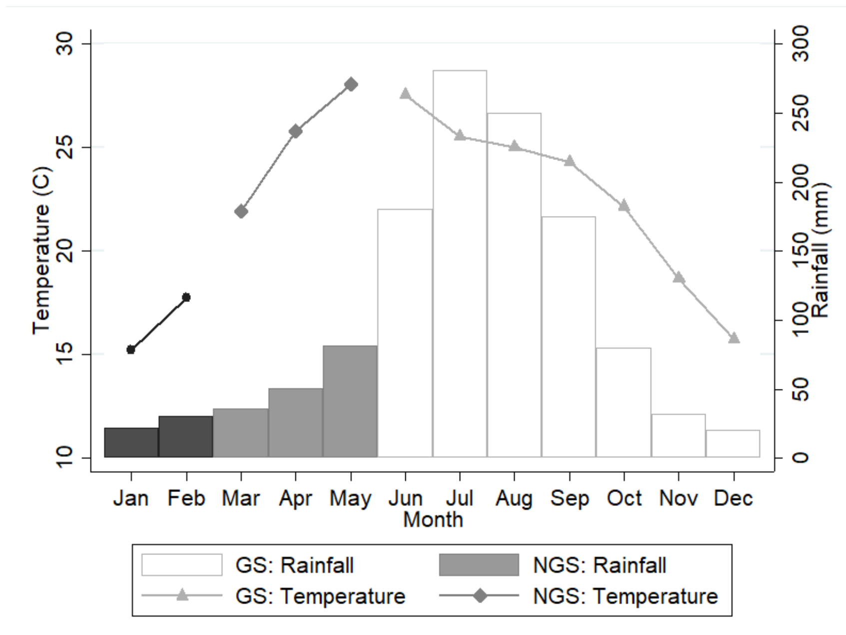


Figure 4.3: Timeline of Effects of Previous Year Temperature and Average Temperatures by Month and Season



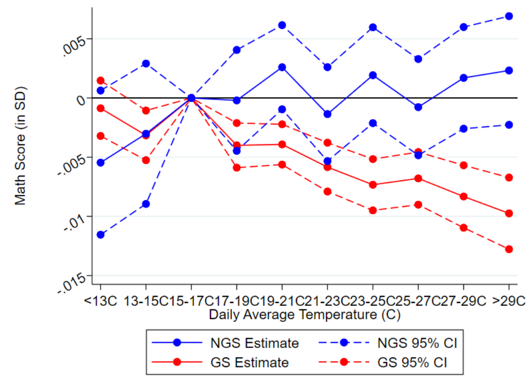
(a) Timeline of Effects of Longer-run Temperature



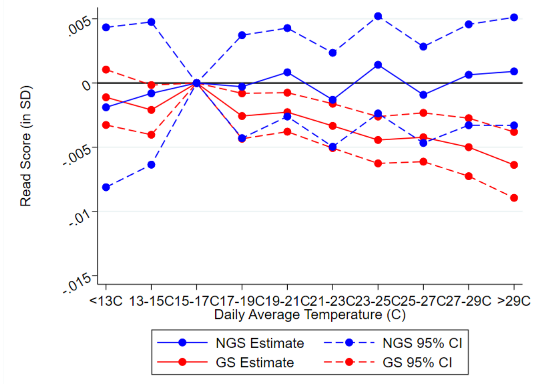
(b) Average Temperatures By Month and Season

Notes: Figure (a) demonstrates the timeline over which the effects of temperature manifest. Figure (b) shows the average temperature by month over the 2006-2014 time period along with average total rainfall in each month. The non-growing season is characterized by low rainfall whereas the growing season is characterized by high rainfall. GS: Growing Season; NGS: Non-Growing Season; PY: Previous Year; CY: Current Year.

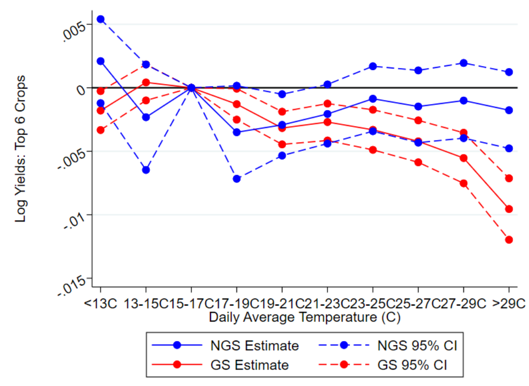
Figure 4.4: Growing Season v. Non-Growing Season: Previous Year Temperature, Test Scores (ASER), and Agricultural Yields



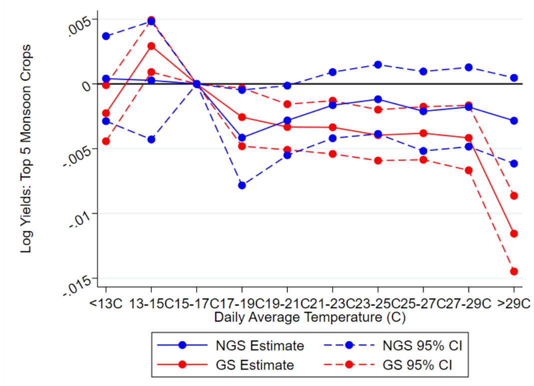
(a) Math Scores



(b) Reading Scores



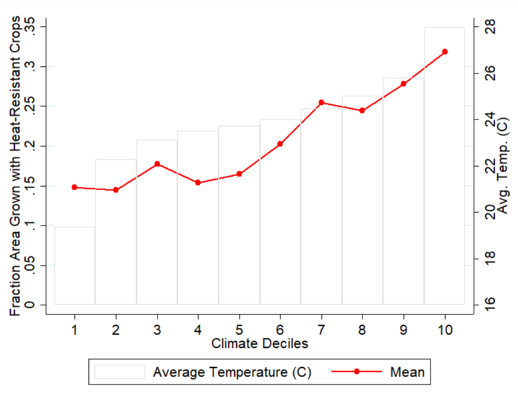
(c) Top 6 Crops



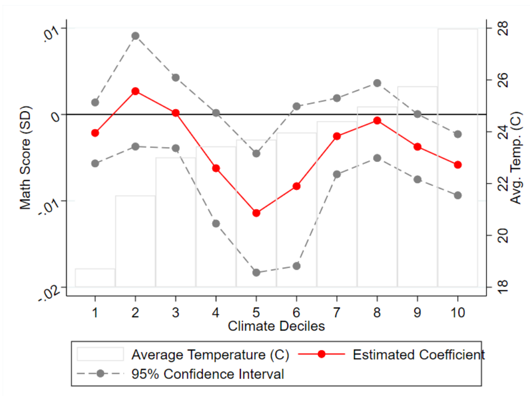
(d) Top 5 Monsoon Crops

Notes: Panel (a) and (b) show the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 4.3) on current year math and reading performance divided amongst the growing season (June—Dec) and the non-growing season (March—May). In panel (c) and (d) the figure shows the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 4.3) on previous year agricultural yields from 1979—2014 divided amongst the growing season (June—Dec) and the non-growing season (March—May). In all panels, the effect of days between 15°C-17°C is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C. The regressions include district and year fixed effects. Panel (a) and (b) also include age fixed effects. We control flexibly for precipitation and humidity. Standard errors are clustered at district level. GS: Growing Season; NGS: Non-Growing Season.

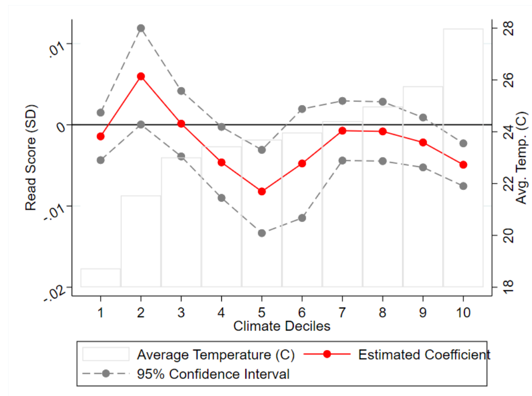
Figure 4.5: Heat-Resistant Crops and Effect of Previous Year Temperature on Test Scores (ASER) by Historical Temperature Deciles



(a) Heat-Resistant Crop Area as a Fraction of Total Cultivated Area



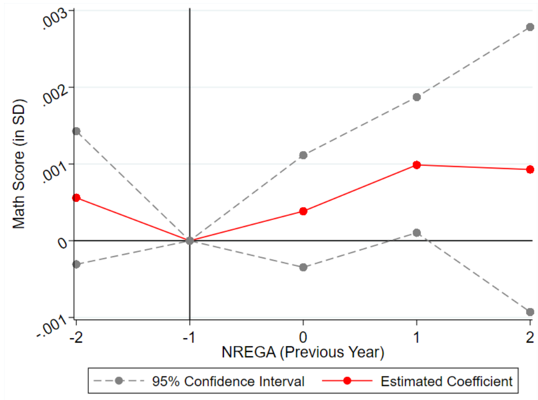
(b) Math Scores



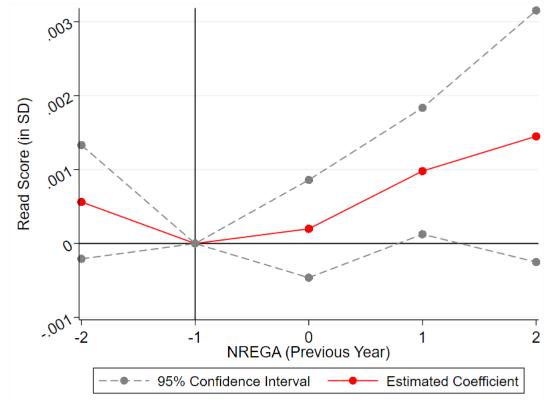
(c) Reading Scores

Notes: Figure (a) shows the average proportion of area within each district that is used to grow heat-resistant crops by deciles of average long-term temperature or the climate normal. Figures (b) and (c) show the the marginal effects of an additional hot day in the previous year (defined as number of days in the previous calendar year—see Figure 4.3) above 21°C on current year math and reading performance respectively by deciles of average long-term temperature, or the climate normal. The effect of days between 15°C-21°C is normalized to zero and coefficients are interpreted relative to 15°C-21°C. The regressions include district, year and age fixed effects. We control flexibly for precipitation and humidity. Standard errors are clustered at the district level.

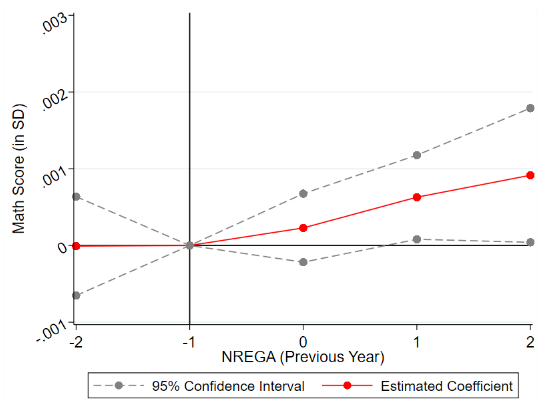
Figure 4.6: Event Study: Previous Year Temperature, NREGA, and Test Scores



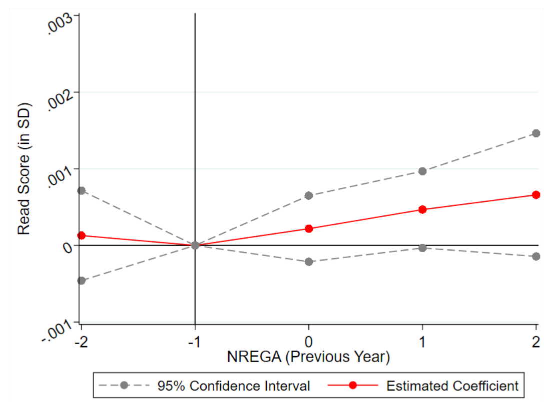
(a) Math Scores: $NREGA(T = \tau) * Days > 29°C$



(b) Reading Scores: $NREGA(T = \tau) * Days > 29°C$



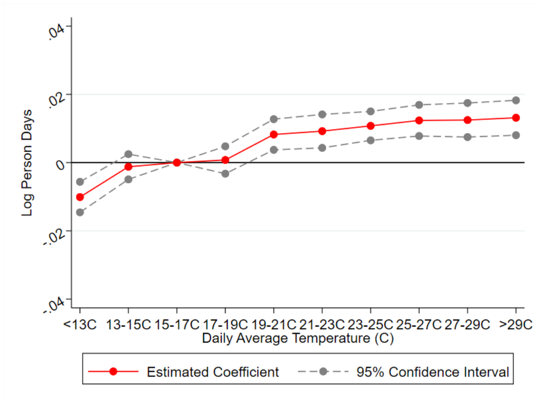
(c) Math Scores: $NREGA(T = \tau) * Days > 21°C$



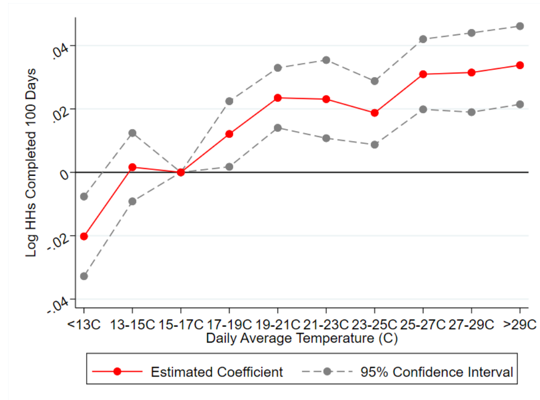
(d) Reading Scores: $NREGA(T = \tau) * Days > 21°C$

Notes: The figure shows the influence of NREGA (in previous year) in attenuating the impact of longer-run temperature (defined as number of days in the previous calendar year—see Figure 4.3) on current year test performance in both math and reading. In Panel (a) and (b) (Panel (c) and (d)) the effect of days between 15°C-17°C (15°C-21°C) is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C (15°C-21°C). In Panel (a) and (b) (Panel (c) and (d)) the omitted variable is the days above 29°C (21°C) in the year prior to the introduction of NREGA ($\tau = -1$). The regressions include district, year and age fixed effects, and control for age-for-grade status. We also control flexibly for precipitation and humidity. Standard errors are clustered at the district level.

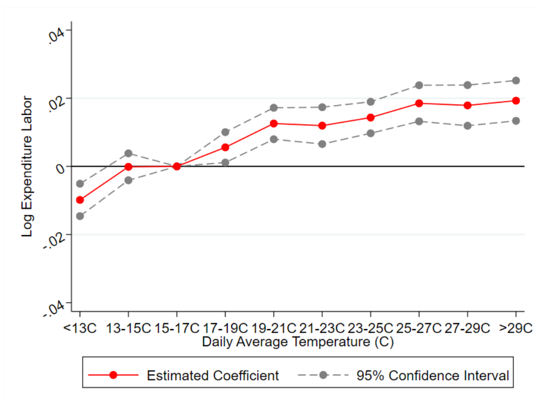
Figure 4.7: Effect of Previous Year Temperature on NREGA Take-Up



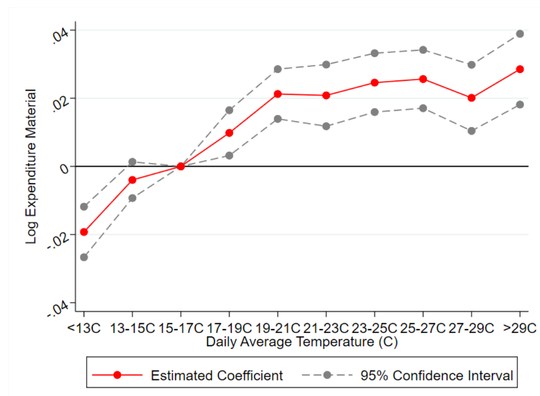
(a) Person Days



(b) HH's Completed All 100 Days



(c) Labor Expenditure



(d) Material Expenditure

Notes: The figure shows the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 4.3) on previous year NREGA take-up, completion, and program expenditures. The effect of days between 15°C-17°C is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C. The regressions include district and year fixed effects. We control flexibly for precipitation and humidity. Standard errors are clustered at the district level.

4.8.2 Tables

Table 4.1: Previous Year Temperature and Test Scores (ASER)

	(1) Math Score (in SD) β / SE	(2) Math Score (in SD) β / SE	(3) Read Score (in SD) β / SE	(4) Read Score (in SD) β / SE
PY Days <15C	-0.0024***		-0.0019***	
	(0.0006)		(0.0006)	
PY Days >21C	-0.0016***		-0.0007*	
	(0.0005)		(0.0004)	
PY Days <13C		-0.0034***		-0.0025***
		(0.0009)		(0.0008)
PY Days 13-15C		-0.0031***		-0.0021***
		(0.0009)		(0.0008)
PY Days 17-19C		-0.0021**		-0.0012
		(0.0008)		(0.0008)
PY Days 19-21C		-0.0008		0.0000
		(0.0007)		(0.0006)
PY Days 21-23C		-0.0027***		-0.0009
		(0.0008)		(0.0007)
PY Days 23-25C		-0.0030***		-0.0014**
		(0.0008)		(0.0007)
PY Days 25-27C		-0.0023***		-0.0011
		(0.0008)		(0.0007)
PY Days 27-29C		-0.0024***		-0.0010
		(0.0009)		(0.0008)
PY Days >29C		-0.0030***		-0.0018**
		(0.0009)		(0.0008)
Observations	4581616	4581616	4581616	4581616
R^2	0.084	0.084	0.068	0.068

Notes: This table shows the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 4.3) on current year math and reading performance using the ASER data set. In Columns (2) and (4) (Columns (1) and (3)), the effect of days between 15°C-17°C (15°C-21°C) is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C (15°C-21°C). The regressions include district, year and age fixed effects. We control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered at the district level. PY: Previous Year.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 4.2: Previous Year, Current Year and Next Year Temperature and Test Scores (ASER)

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
PY Days <15C	-0.0030***	-0.0027***
	(0.0007)	(0.0006)
PY Days >21C	-0.0020***	-0.0008*
	(0.0005)	(0.0005)
CY Days <15C	-0.0004	-0.0008
	(0.0007)	(0.0006)
CY Days >21C	0.0012*	0.0002
	(0.0006)	(0.0005)
NY Days <15C	-0.0006	-0.0017***
	(0.0007)	(0.0006)
NY Days >21C	0.0007	0.0001
	(0.0006)	(0.0005)
Observations	4182681	4182681
R^2	0.088	0.071

Notes: This table shows the effect of previous year (defined as number of days in the previous calendar year—see Figure 4.4(a)), current year, and next year temperature on current year math and reading performance using the ASER data set. The effect of days between 15°C-21°C is normalized to zero and all other coefficients are interpreted relative to 15°C-21°C. The regressions include district, year and age fixed effects. We control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered at the district level. PY: Previous Year; CY: Current Year; NY: Next Year. *Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 4.3: Longer-Run Temperature and Test Scores (YLS)

	(1) Math Score (in SD) β / SE	(2) Math Score (in SD) β / SE	(3) PPVT Score (in SD) β / SE	(4) PPVT Score (in SD) β / SE
Days Between Two Tests >23C	-0.003***		-0.004***	
	(0.001)		(0.001)	
Day-of-Test >23C	-0.114***		0.042	
	(0.043)		(0.057)	
Days Between Two Tests 23-25C		-0.007***		0.000
		(0.001)		(0.002)
Days Between Two Tests 25-27C		-0.002**		-0.007***
		(0.001)		(0.002)
Days Between Two Tests >27C		-0.007***		-0.007***
		(0.001)		(0.002)
Day-of-Test 23-25C		-0.088**		0.006
		(0.044)		(0.056)
Day-of-Test 25-27C		-0.164***		0.153**
		(0.056)		(0.076)
Day-of-Test >27C		-0.133*		0.252***
		(0.075)		(0.092)
Observations	2604	2604	2541	2541
R^2	0.058	0.071	0.077	0.091

Notes: This table shows the effect of temperature (defined as number of days in a given bin between successive tests) on math and reading performance using the YLS data set. The effect of days below 23°C is normalized to zero and all other coefficients are interpreted relative to below 23°C. The regressions include individual, day of week, month, and survey round (age) fixed effects. We control for day-of-test temperatures, and both cumulative and day-of-test precipitation as well as cumulative and day-of-test precipitation and humidity. Standard errors are in parentheses, clustered by district-week.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 4.4: Heat-Resistant Crops (HRC): Previous Year Temperature and Test Scores (ASER)

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
PY Days <15C	-0.0026***	-0.0020***
	(0.0007)	(0.0006)
PY Days >21C	-0.0031***	-0.0015***
	(0.0006)	(0.0005)
PY Days >21C * HRC	0.0021***	0.0009
	(0.0007)	(0.0006)
Observations	4403838	4403838
R^2	0.083	0.069

Notes: This table shows the effect of temperature (defined as number of days in the previous calendar year—see Figure 4.3) on current year math and reading performance by districts that grow heat-resistant using the ASER data set. In all specifications, the effect of days between 15°C-21°C is normalized to zero and all other coefficients are interpreted relative to 15°C-21°C. All specifications include district, year, and age fixed effects. We control for precipitation and humidity in all specifications. Standard errors are in parentheses, clustered by district. PY: Previous Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 4.5: Event Study: Previous Year Temperature, NREGA, and Test Scores (ASER)

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
NREGA: T = -3	-0.0269	0.0068
	(0.0373)	(0.0338)
NREGA: T = -2	-0.0216	-0.0255
	(0.0342)	(0.0316)
NREGA: T = 0	-0.0841***	-0.0585**
	(0.0257)	(0.0239)
NREGA: T = 1	-0.1385***	-0.1187***
	(0.0342)	(0.0325)
NREGA: T = 2	-0.1278**	-0.1379**
	(0.0600)	(0.0553)
PY Days <13C	-0.0031**	-0.0014
	(0.0015)	(0.0013)
PY Days 13-15C	-0.0009	-0.0013
	(0.0017)	(0.0015)
PY Days 17-19C	0.0028*	0.0024
	(0.0016)	(0.0015)
PY Days 19-21C	0.0027**	0.0021*
	(0.0014)	(0.0013)
PY Days 21-23C	0.0020	0.0014
	(0.0014)	(0.0012)
PY Days 23-25C	0.0015	0.0012
	(0.0014)	(0.0012)
PY Days 25-27C	-0.0001	-0.0001
	(0.0015)	(0.0013)
PY Days 27-29C	-0.0002	-0.0001
	(0.0016)	(0.0014)
PY Days >29C	-0.0017	-0.0012
	(0.0017)	(0.0015)
NREGA: T = -3 * PY Days >29C	0.0009*	0.0003
	(0.0005)	(0.0005)
NREGA: T = -2 * PY Days >29C	0.0006	0.0006
	(0.0004)	(0.0004)
NREGA: T = 0 * PY Days >29C	0.0004	0.0002
	(0.0004)	(0.0003)
NREGA: T = 1 * PY Days >29C	0.0010**	0.0010**
	(0.0005)	(0.0004)
NREGA: T = 2 * PY Days >29C	0.0009	0.0014*
	(0.0009)	(0.0009)
Observations	1866623	1866623
R^2	0.177	0.168

Notes: This table shows the influence of NREGA (in previous year) in attenuating the effects of longer-run temperature (defined as number of days in the previous calendar year—see Figure 4.3) on current year math and reading performance. The effect of days between 15°C-17°C is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C. The omitted variable is the days above 29°C in the year prior to the introduction of NREGA ($\tau = -1$) The regressions include district, year and age fixed effects, and control for age-for-grade status. We also control flexibly for precipitation and humidity. Standard errors are clustered at the district level. PY: Previous Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 4.6: Event Study: Previous Year Temperature, NREGA, and Test Scores (ASER)

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
NREGA: T = -3	0.3797***	0.2525***
	(0.0915)	(0.0902)
NREGA: T = -2	0.0052	-0.0331
	(0.0996)	(0.0914)
NREGA: T = 0	-0.1073	-0.0920
	(0.0676)	(0.0654)
NREGA: T = 1	-0.2285***	-0.1742**
	(0.0834)	(0.0768)
NREGA: T = 2	-0.2840**	-0.2178*
	(0.1266)	(0.1190)
PY Days <15C	-0.0047***	-0.0037***
	(0.0011)	(0.0010)
PY Days >21C	-0.0011	-0.0008
	(0.0008)	(0.0007)
NREGA: T = -3 * PY Days >21C	-0.0013***	-0.0008***
	(0.0003)	(0.0003)
NREGA: T = -2 * PY Days >21C	-0.0000	0.0001
	(0.0003)	(0.0003)
NREGA: T = 0 * PY Days >21C	0.0002	0.0002
	(0.0002)	(0.0002)
NREGA: T = 1 * PY Days >21C	0.0006**	0.0005*
	(0.0003)	(0.0003)
NREGA: T = 2 * PY Days >21C	0.0009**	0.0007
	(0.0004)	(0.0004)
Observations	1866623	1866623
R^2	0.177	0.167

Notes: This table shows the influence of NREGA (in previous year) in attenuating the effects of longer-run temperature (defined as number of days in the previous calendar year—see Figure 4.3) on current year math and reading performance. The effect of days between 15°C-21°C is normalized to zero and all other coefficients are interpreted relative to 15°C-21°C. The omitted variable is the days above 21°C in the year prior to the introduction of NREGA ($\tau = -1$) The regressions include district, year and age fixed effects, and control for age-for-grade status. We also control flexibly for precipitation and humidity. Standard errors are clustered at the district level. PY: Previous Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Chapter 5

Within-Season Producer Response to Warmer Temperatures: Defensive Investments by Kenyan Farmers

5.1 Introduction

With short-run weather risk – e.g., due to extreme events like heat waves – widely projected to grow in the years ahead due to climate change, it is crucial to know how well and quickly farmers in low-income countries adjust to exogenous shocks to production. This question has interested development and agricultural economists for decades, at least since (350), (21) and (152). More recently, environmental economists have begun to explore this issue, recognizing that agricultural damages induced by global warming may be especially problematic for farmers in low-income countries who rely on traditional methods for weather forecasting and may be unable to detect a change in temperature or to respond promptly even to changes they notice, for example due to binding financial liquidity constraints. But if farmers indeed detect and quickly adjust to warming temperatures on their own, the resulting damages could be contained. Therefore, understanding how and how fast farmers adapt to temperature shocks can usefully inform allocation of scarce public resources to build resilience and avoid permanent damage.

In this paper we use household-level panel data from maize farmers in Kenya, and temperature data disaggregated across different stages of the crop growth cycle, to investigate if and how farmers adjust agricultural inputs in response to within-season temperature variation. Exploiting plausibly exogenous variation in temperature at the village level after absorbing fixed village level attributes (i.e., controlling for village fixed effects) as well as time varying province level characteristics (province-by-year fixed effects), we show that Kenyan farmers respond promptly to temperature variation. More specifically, they increase pesticide use in response to heat-induced increased biotic stress from diseases and pests that are most effectively addressed soon after emergence, early in the season. And farmers increase weeding effort throughout the season in response to higher temperatures that promote weed growth. Meanwhile, farmers reduce inorganic fertilizer use early in the growing season, contemporaneously with increased pesticide use. That could be a response to increased yield risk, or binding financial liquidity constraints inducing trade-offs among input expenditures, or both. Farmers expressly identify warmer temperatures as a threat to maize productivity due to greater incidence of pests, weeds and crop diseases. And they undertake defensive investments quickly in response to short-run temperature shocks.

More precisely, we find that 10 extra growing degree days (GDD) over 8C during the initial vegetative growth stage increases the proportion of farmers using pesticides by around 10%, and reduces the proportion using inorganic fertilizer by approximately 2%, compared to the baseline. Similarly, a 10 day increase in GDD increases pesticide application rates per acre by roughly 20%, while reducing fertilizer application rates by over 10%. And 10 extra GDD during the pre-planting phase increases weeding labor by 0.2 days. Because most farmers report financial liquidity constraints limit their purchase of inputs, temperature shocks may confront farmers with a trade-off between defensive investments in pesticides and weeding labor, versus yield-increasing fertilizers. Farmers' responsiveness to short-run temperature shocks also appears positively associated with wealth, as reflected in land holdings.[1] Overall, our results are consistent with a model in which farmers make production decisions sequentially, promptly adjusting to new information as it arrives within season, subject to financial constraints.

These findings are noteworthy as well because the maize growing regions of Kenya fall in temperate zones in which warming temperatures are widely anticipated to boost staple crop yields through higher temperatures accelerative effect on photosynthesis. Average daily temperatures in the villages we study range from 12-29C (Figure 5.1), a range over which maize yields typically increase with warming temperatures. In fact, the 99th percentile of the distribution of daily *maximum* temperatures for villages in our sample is 32C (Figure 5.2). Maize only declines physiologically due to heat stress above 29-30C

[1] This result is consistent with numerous papers that show that financial constraints faced by farmers in low-income countries inhibit the adoption of modern agricultural inputs (e.g., (102; 123; 278; 332)).

(249; 345). Large swaths of maize farms in Africa fall in similar agro-ecological zones (Figure 5.3). Because these Kenyan households' maize crops are unlikely to experience direct, abiotic heat stress from the modest warming observed in the data – and anticipated in coming years – any adverse effects on agriculture, and consequent margins of adjustment, almost surely result from indirect, biotic stresses arising from the temperature response of pests and pathogens.

In investigating if maize farmers in Kenya adapt in the short run to within-season temperature variation, we contribute to two related literatures. First, a longstanding literature shows that farmers in low-income countries can and do adjust production decisions quickly, adapting to new information as it emerges (21; 152; 350). This paper appears to be the first since (152) to empirically investigate if farmers promptly adjust their input allocation in response to exogenous shocks to production. However, while (152) evaluates farmer response to initial rainfall in Burkina Faso, we examine how and how fast do Kenyan farmers adjust their inputs in response to warmer temperatures during the growing season.

Second, this paper also contributes to a large environmental economics literature on agricultural adaptation to climate change. Within this literature, few studies examine how farmers adjust to higher than normal temperatures in developing countries (e.g., (236; 237; 238; 353)).[2] These papers typically rely on cross-sectional variation to compare longer-run outcomes such as irrigation and crop choice in hot versus cold areas. While the cross-sectional approach approximates the ideal climate change experiment, omitted variables concerns in this approach mean that the average climate could be correlated with other fixed,

[2] A number of papers have examined the extent of adaptation rather than how farmers adjust to warming temperatures (e.g., (268); (343); (127); (128) (345); (119); (375); (71)). However, among these only (375) examines agricultural adaptation in a developing country, India.

unobserved factors. In this paper, we exploit plausibly exogenous short-run variation in weather to examine within-season adjustments in agricultural inputs. If farmers promptly adapt input applications within season in response to warmer temperature that differentially affect crop growth across different stages in the agricultural cycle – both directly through plant physiological effects of temperature and indirectly through temperature-induced changes in the supporting agro-ecology – then any analyses based on seasonal or annual temperature variation may miss important behavioral responses in the short-run. Moreover, if farmers can adjust in the short run, it is more plausible that they will also be able to adjust in the long run using methods unavailable to them in the short run.[3] Lastly, this literature has also overlooked farmer defensive investments arising not due to heat stress but rather due to biotic stresses arising from broader agroecological response to warmer weather. To our knowledge, this is the first economics study to isolate this mechanism behind farmer adaptation to temperature.

The remainder of the paper proceeds as follows. In Section 5.2 we provide background on relevant ecological and agronomic literatures, and briefly discuss the role of credit and insurance markets in agricultural technology adoption in poor countries. Section 5.3 describes the data. In Section 5.4 we outline the empirical strategy and our main results for the effects of temperature on agricultural input decisions. Finally, Section 5.5 offers concluding remarks.

[3] For example, (339) famously argues that the Le Chatelier principle implies that demand and supply elasticities are lower in the short run than in the long run because of the quasi-fixed-cost constraint that binds only in the short run.

5.2 Background

5.2.1 Temperature, Pests, Weeds and Pesticides

The dependence of plant diseases and pests on weather is well-known amongst plant pathologists and entomologists (e.g., (91; 99; 165)). For that reason, the broader ecological literature concludes that climate change will increase challenges to agriculture from pests, weeds and diseases, in part due to higher than normal temperatures (e.g., (312); (327)).

For instance, grey leaf spot is a major maize fungal disease in Kenya. It was first reported in Kenya during 1995, and small-scale farmers have continued to experience considerable yield losses from grey leaf spot (360). Infection and growth of grey leaf spot are most likely to occur following a humid and warm period. Specifically, at 100% relative humidity, the optimum temperature for sporulation is between 25-30C. Similarly, the highest rates of lesion expansion were observed at 25C and 30C (314). Experiments indicate that fungicide treatment should be initiated after the disease was observed but before high levels were present (418). So higher temperatures could increase gray leaf spot incidence and induce early season adaptive responses by farmers. Delayed response to fungal infection is typically ineffective and thus a poor use of scarce resources.

Similarly, insect behavior, distribution, development and survival are strongly coupled with environmental conditions, especially temperature, since insects do not use their metabolism to control their body temperature, but rather depend on ambient air temperature. Global warming will favor insect proliferation and increase the incidence and severity of insect-related damages in maize (76).

The most common insect maize pest in Kenya is the stem borer. Damage caused by stem borers is one of the main causes of low maize yields (366). Lepidopteran stem borers such as the indigenous noctuids Busseola fusca (Fuller) and Sesamia calamistis (Hampson) and the exotic crambid Chilo partellus (Swinhoe) attack the maize crop in East Africa: larval survival rates across these stem borer species is highest at 20C.[4] On the other hand, growth rates for Busseola fusca (Fuller), Sesamia calamistis (Hampson), and Chilo partellus (Swinhoe) are highest at 30C, 25C, and 20C, respectively, and lowest at 15C (294). Female stem borer moths lay eggs on maize leaves. The newly emerged larvae enter into the whorls of young maize plants and feed actively on the tender leaves. Later, the larvae bore into the stem and start tunneling. Stem borers can be controlled by applications of insecticides to the leaf whorl early in crop growth cycle to kill early larval instars; this method has limited effectiveness once the larvae bore into the stem (169). So as with gray leaf spot disease, the stem borer pest pressure on maize in Kenya should increase with higher temperatures, inducing early season response through pesticide application.

Weeds compete with crops for nutrients, moisture, light and space, adversely affecting crop yields. Weed growth is also influenced by abiotic conditions such as temperature and humidity (144; 317; 361). For instance, milder winters are likely to increase the survival of some winter annual weeds, whereas warmer summers may allow other type of weeds to grow in previously inhospitable regions (60; 189; 415). Weed control during the first weeks after planting

[4]Busseola fusca (Fuller) has higher survival rates at 30C than at 25C. Sesamia calamistis (Hampson) and Chilo partellus (Swinhoe) have higher survival rate at 25C than at 30C (294).

is crucial because weeds compete vigorously with the maize crop for nutrients and water during this crucial period of plant growth (139). Extension recommendations call for maize fields to be kept weed-free for the first 56 days after planting to achieve maximum yields (11). One week's delay in first weeding may reduce maize yields by as much as one-third (298). Very early in the season, weed control among small farmers in Kenya is typically accomplished with household labor. But if weed growth is aggressive, farmers might use herbicides - a pesticide targeted specially at weeds before planting or in the early post-planting stage as a substitute for weeding labor (170). Once the crop is established, however, any further weed control requires additional labor effort, which continues nearly until harvest. As with maize disease and pests, higher temperatures are thus expected to induce greater weed competition with crops, forcing farmers to devote more labor and pesticides to combating weeds. The effects of warmer temperatures on manual weeding may extend deeper into the growing season as farmers can adjust labor inputs later in the season. These predictions from the agro-ecological literature mirror what we find in the data.

5.2.2 Fertilizer Use Under Liquidity Constraints and Risk

Higher than normal temperatures increase the prevalence of pests and diseases, plausibly forcing farmers to increase defensive investments on loss-reducing inputs like pesticides (e.g., herbicides, insecticides, fungicides) and diverting resources from productivity-enhancing technologies like fertilizer. Such effects on fertilizer uptake might be driven by ex ante credit constraints that compel poor farmers to trade off expenditures in one area for another.

Alternatively, farmers might anticipate increased risk of crop losses and reduce the capital they put at risk through fertilizer purchases. These two effects are not mutually exclusive and can be difficult to fully disentangle. For instance, (332) show that poor farmers facing increased rainfall variability tend to hold a portfolio that is less influenced by rainfall, although wealthier farmers facing varying exposure to risk do not exhibit changing portfolios of investments. More recently and nearby, (123), find that both ex ante credit constraints and the possibility of low consumption outcomes when harvests fail discourage the application of fertilizer in Ethiopia.

Typically, maize farmers apply fertilizer twice. Basal fertilizer applications occur at planting. Top dressing fertilizer application occurs after plant emerges but seldom without basal fertilizer application. But if fertilizer is used at planting, top dressing often occurs post-germination, roughly 4-6 weeks into the growing season. Thus, if farmers promptly adjust to new information (21; 152),[5] these effects should respond primarily to temperature shocks during the preplanting or early vegetative growth phase. This is particularly true in our context, as agricultural input markets in Kenya are relatively well-developed compared to other countries in sub-Saharan Africa (358), and because Kenyan farmers usually buy fertilizer just before applying it (143).

[5](134) shows that within-season measures of the subjective probability distributions that farmers hold dictate the effectiveness of policies intended to support agrarian households.

5.3 Data

We use a qualitatively rich, household-level panel data set, representative of farmers in Kenya's main maize cultivating provinces. We augment these with detailed village level data with daily weather variables including temperature, rainfall, humidity and soil moisture.

5.3.1 Household Data

The household panel survey data are representative of the main maize-growing areas in Kenya. The survey was designed and implemented under the Tegemeo Agricultural Monitoring and Policy Analysis (TAMPA) project, a collaboration among Tegemeo Institute of Egerton University, Michigan State University, and the Kenya Agricultural Research Institute. Figure D.1 maps the survey villages across Kenya. These villages were selected randomly from each of eight predetermined agro-economic zones and then households were sampled randomly from each selected village. We use data from a balanced panel of 1242 households collected over five rounds: 1996-97, 1999-00, 2003-04, 2006-07, and 2009-10. The survey includes detailed agricultural input and output data, demographics, credit and infrastructure information. The 2009-10 round collected rich subjective data on farmers perceptions of the impacts of changes in temperature, as well as reasons for non-adoption of fertilizer. Villages were geo-referenced, allowing us to merge the household data with daily temperature, precipitation, relative humidity and soil moisture data at the village level as well as agro-ecological zone crop calendars.

Table D.1 presents summary statistics for our balanced sample from 1997-2010. ‘Pesticide 0/1’ and ‘Pesticide/Acre(kgs)’ capture the uptake rate and application intensity of pesticide use (irrespective of take-up) during the main growing season, respectively.[6] These detailed data were only collected in 2003-04, 2006-07, and 2009-10. While answering questions on inputs, respondents often used pesticides and specific pests, weeds and disease repellents (e.g., herbicide, insecticide, fungicide) interchangeably. Therefore, our measure of pesticide use takes the binary value of 1 if a farmer uses any chemical or biological agent that protects crops from pests, weeds or crop diseases, and 0 otherwise. Almost 30% of households in our balanced panel adopted some variety of pesticides in 2003, use then increased to 65% in 2006, before dropping off somewhat to 50% in 2009. The average maize farmer used 0.25 kg/acre of pesticides in 2003, increasing to over 0.5 kg/acre by 2009. ‘Own Weeding Days/Acre’ indicates the average number own (household) labor days spent in weeding activities. ‘Fertilizer 0/1’ depicts the uptake of inorganic fertilizer in the main growing season, 1997-2010. Fertilizer use is high amongst maize farmers in rural Kenya. In 1997, almost 65% of households used fertilizer, while the corresponding figure is 75% for 2010. The average maize farmer used around 45 kgs/acre in 1997. Average quantity use then increased to over 55 kgs/acre in 1999, before dropping to 50 kgs/acre in 2009. Lastly, ‘Maize Output/Acre(kgs)’ captures average maize yields over time.

Finally, Tables D.2 and D.3 show household-level transitions of pesticide and fertilizer use in the data, with 30% (60%) of households switching into or out of fertilizer (pesticide) use across survey rounds. So there is clearly considerable across-round variation in input use patterns by Kenyan maize farmers around

[6] We assume all pesticides to have the same density and convert all units to kilograms (kgs).

the broader trend of expanding purchased input use over time. We exploit the inter-temporal variation in household-specific input use to identify the causal effects of temperature shocks within specific periods of the growing season on farmer defensive investments in preventing crop loss due to biotic stresses and any contemporaneous adjustment in productivity-enhancing fertilizer investments.

5.3.2 Kenyan Maize Calendar

To uncover the underlying mechanisms that influence farmer climate adaptation strategies, and plausibly related spillover effects on productivity-enhancing inputs, we need to disaggregate the main growing season. So as to parse the information set available to farmers as they make sub-season-specific input use choices, we use maize crop calendars specific to each sub-agro-ecological zone (AEZ) in Kenya, obtained from the Food and Agriculture Organization (FAO) of the United Nations, and broken into three distinct stages of the agricultural cycle.[7] This calendar gives the usual start and end dates of the planting period and harvest period for each sub-AEZ and for long and short rainy seasons. We use the calendar for the long rainy season, which is the main growing season. We define as the 'pre-planting' period the two months right before planting begins, with or without basal fertilizer application. Land preparation occurs during this pre-planting period, sometimes including clearing weeds.[8] We define the four to six weeks right after planting as the initial post-planting period. This is the

[7] The maize calendar was downloaded from http://www.fao.org/agriculture/seed/cropcalendar/welcome.do.

[8] Please see http://nafis.go.ke/agriculture/maize/establishment-of-maize/ for recommendation on land preparation and http://www.nafis.go.ke/agriculture/maize/field-management-practices/ for recommendation on fertilizer application.

recommended period for top dressing application of fertilizer. Thus, the three phases of the main agricultural cycle are: 1) 'PP': land preparation period (from onset of pre-planting to onset of planting) 2) 'GS1': planting and basal fertilizer application period (the initial post-planting period from onset of planting to onset of top dressing fertilizer application), and 3) 'GS2': post-planting top dressing fertilizer application period (after top dressing fertilizer to onset of harvest) (Figure D.2).

Kenya's topography is quite heterogeneous (Figure D.3). There exist substantial heterogeneity in agro-ecological zones that span the villages in our data. Table D.4 provides maize crop calendar specific to each province in Kenya, broken into three stages of the agricultural cycle described above.[9] Although there exist differences in the maize crop calendar within provinces, discrepancies in the maize crop calendars across provinces are far more significant. Therefore, our baseline econometric specification includes village and province-by-round fixed effects. Any remaining temperature variation pertains only to within-province-round deviations from village means. For example, the amount by which western parts of Nyanza province are warmer than normal in a given survey round in GS1, compared to how much eastern Nyanza is warmer than normal in the same round in GS1.

There exist almost no differences in the maize crop calendar within districts. In robustness checks, we show our results are robust to the inclusion of district-by-round fixed effects where the remaining temperature variation pertains only to within-district-round deviations from village means. In addition, we show our point estimates are largely unaffected when we assign a uniform maize

[9]Growing degree days are calculated holding maize crop calendars fixed across survey-rounds. Therefore, growing degree days do not vary due to potentially endogenous weather-induced changes to the maize crop calendar from year to year.

crop calendar to all villages in the Western, Coast, Central, Nyanza, and Rift Valley province and a uniform maize crop calendar to all villages in the Eastern province, as well as when we subsequently drop the Eastern province from our sample.

5.3.3 Weather Data

Because of the incomplete coverage of ground weather stations in Kenya, we use daily temperature, precipitation, relative humidity and soil moisture data from various gridded and satellite data sets. Daily temperature data are from the ERA-Interim Reanalysis archive, which is constructed by researchers at the European Centre for Medium-Term Weather Forecasting. It is a gridded reanalysis data set providing information on average daily temperature on a 1 degree x 1 degree latitude-longitude grid, from 1979 to present day (118). A point shapefile for each village in the TAMPA sample was used to generate the value of each point for each daily temperature pixel it intersects with. We generated a table containing daily temperature values for each village coordinate point for our study period. Similarly, we generated daily precipitation data from the Climate Hazards Group InfraRed Precipitation Station (CHIRPS) data set of daily 0.5 degree resolution gridded data for all of Africa.[10] Daily relative humidity data came from NASA.[11] These satellite and model derived solar and meteorological data cover the global surface at 1 degree x 1 degree resolution. Lastly, daily soil moisture data are sourced from the European Space Agency. This global soil moisture data set has been generated using active and passive microwave spaceborne instruments and covers the 37 year period from 1978 to

[10] CHIRPS was downloaded from http://chg.geog.ucsb.edu/data/chirps/

[11] The relative humidity data are from https://power.larc.nasa.gov/cgi-bin/agro.cgi?na

2015. It provides daily surface soil moisture with a spatial resolution of 0.25 degrees.[12]

From daily data, we generate aggregate weather indicators for each stage of the crop growth cycle, across five rounds of the TAMPA data. For our primary variable of interest, temperature, we use the concept of cumulative growing degree days (GDD). GDD measures the intensity of daily exposure to temperatures above a lower bound, beneath which cold stress might impede plant growth, and below an upper bound at which heat stress might begin, to estimate the effects of temperature on fertilizer and pesticide use, as well as weeding labor days. The literature has demonstrated the relationship between temperature and agricultural outcomes using GDDs (249; 343; 345). We use daily average temperatures to calculate the number of days each village is exposed to temperatures above a lower bound (8C), and below an upper bound (30C), and then sum these daily exposures for each of the three phases during the main growing season for those bounds. $GDD_{8,30}$ represents a typical measure used to predict maize development rates (249), and is perfectly correlated with average growing-season temperature: we do not observe any temperatures below 8C. And average daily temperatures in the data are less than 30C (Figure 5.1).[13] Figure D.4 shows the distribution of daily average temperatures in each phase of the agricultural cycle during the main growing season for all villages in the TAMPA data. Table D.5 presents summary statistics for GDD above 8C in each phase of the agricultural cycle for all five rounds of the household survey.

[12]The soil moisture data are downloaded from http://www.esa-soilmoisture-cci.org/node/145

[13]In fact, the 99th percentile of the distribution of *maximum* daily temperatures for villages in our sample is 32C (Figure 5.2). This is significant since optimum maize growth occurs at temperatures of 24-30C (319). Relatedly, (345) and (249) find that maize yields only decline physiologically due to heat stress above 29-30C.

5.4 Temperature and Agricultural Input Use Response

Almost 50% of households in this sample reported having noticed a change in temperature in the last 10 years, and over 80% of those households indicated that they were affected by said change (Table D.6).[14] If higher temperatures increase the incidence of pests, weeds and diseases, then farmers may incur greater adaptive expenditures on pesticides and weeding labor, and simultaneously reduce use of productivity enhancing fertilizer due to financial constraints, as just explained. Indeed, the qualitative evidence from the TAMPA data set supports such an explanation: almost 40% of maize-farmers affected by changes in temperature pointed to an increase in the incidence of pests, weeds and crop diseases as one of the primary consequences of changes in temperature (Table D.7). Close to 60% of all non-adopters of fertilizer pointed to financial constraints as the reason for non-adoption (Table D.8).

In this section, we formally test the hypothesis that temperature variation during the growing season induces prompt agricultural input adjustments among maize farmers in Kenya. We rule out alternative mechanisms in Appendix D.1.

[14] Figure D.5 presents the historical temperature trends for villages in the TAMPA data and shows that average yearly temperatures have increased in the last 10 years.

5.4.1 Research Design

To examine the effect of temperature on agricultural input use, we estimate the following model:

$$\begin{aligned} Y_{ijdqt} = \beta_1(GDD_{8,30})^{PP}_{jdqt} + \beta_2(GDD_{8,30})^{GS1}_{jdqt} + \\ \beta_3(GDD_{8,30})^{GS2}_{jdqt} + f(Rain)^{PP}_{jdqt} + f(Rain)^{GS1}_{jdqt} \\ + f(Rain)^{GS2}_{jdqt} + \alpha_j + \mu_{qt} + \epsilon_{ijdqt} \end{aligned} \tag{5.1}$$

Y_{ijdqt} is fertilizer or pesticide use (a binary variable equal to one if pesticides were used) for household i in village j, in district d in province q in round t. We control for cumulative rainfall using upper and lower tercile indicators calculated for each period in the agricultural cycle using daily data, and include village fixed effects (α_j). We also include province-by-round fixed effects (μ_{qt}) to control for unobservables that vary by province over time, such as input prices or seasonal climate forecasts. $(GDD_{8,30})_{jdqt}$ is the sum of degree days over 8C during each stage of the main growing season in Kenya.[15] For example, β_1 represents the marginal effect of an extra growing degree day during the pre-planting phase.

We also estimate a second, more flexible model of the effects of temperature

[15]In Section 5.4.2, we demonstrate that our results are robust to the choice of lower bound used to calculate growing degree days.

on agricultural input use:

$$\begin{aligned}
Y_{ijdqt} &= \beta_2 T(18C-19C)^{PP}_{jdqt} + \beta_3 T(19C-20C)^{PP}_{jdqt} + \beta_4 T(20C-21C)^{PP}_{jdqt} \\
&+ \beta_5 T(21C-22C)^{PP}_{jdqt} + \beta_6 T(>22C)^{PP}_{jdqt} \\
&+ \gamma_2 T(18C-19C)^{GS1}_{jdqt} + \gamma_3 T(19C-20C)^{GS1}_{jdqt} + \gamma_4 T(20C-21C)^{GS1}_{jdqt} \\
&+ \gamma_5 T(21C-22C)^{GS1}_{jdqt} + \gamma_6 T(>22C)^{GS1}_{jdqt} \\
&+ \alpha_2 T(18C-19C)^{GS2}_{jdqt} + \alpha_3 T(19C-20C)^{GS2}_{jdqt} + \alpha_4 T(20C-21C)^{GS2}_{jdqt} \\
&+ \alpha_5 T(21C-22C)^{GS2}_{jdqt} + \alpha_6 T(>22C)^{GS2}_{jdqt} \\
&+ f(Rain)^{PP}_{jdqt} + f(Rain)^{GS1}_{jdqt} + f(Rain)^{GS2}_{jdqt} + \alpha_j + \mu_{qt} + \epsilon_{ijdqt} \qquad (5.2)
\end{aligned}$$

The notation is the same as in Equation 5.1. The key difference is our coefficients of interest: T(.). Temperature bins or T(.) are counts of the number of the days in each stage of the main growing season with average daily temperature within the specified range. For example, $T(20C-21C)^{GS1}_{jdqt}$ is the number of days in the initial vegetative growth phase (GS1) with average daily temperature between $20C$ and $21C$. The coldest temperature bin is a count of the number of days with average temperature less than 18C, and the hottest temperature bin is a count of the number of days with average temperature greater than 22C. We chose these endpoints because 18C and 22C are the 20th and 80th percentiles of average daily temperatures across villages in the TAMPA sample from 1990 to 2012. The bins in between are evenly spaced one degree apart. The omitted bin is the <18C bin, which we chose to omit because it has the maximum (minimum) coefficient of all the bins for fertilizer use (pesticide use and weeding labor). All other bins are interpreted relative to this bin. For example, γ_6, the coefficient on the hottest bin, is the marginal effect on agricultural inputs of an extra day with average temperature greater than $> 22C$ in GS1 relative to a day with average temperature below $18C$ in GS1. In estimating this flexible approach we follow prior work in climate economics and avoid imposing restrictive assumptions on the functional relationship between temperature and agricultural production decisions (205).

We cluster standard errors at the village level. The identifying assumption is that changes in temperature experienced by a village during each phase of the agricultural cycle is exogenous to unobservable household or village level characteristics that vary over time. The assumption is plausible given the randomness of weather fluctuations and the inability of rural households to predict such fluctuations beyond common spatial features such as season climate forecasts which we control for with province-by-round fixed effects (μ_{qt}). As robustness checks, we also control for time-invariant household level characteristics (e.g., farming skill, access to groundwater, education, relationship with input suppliers), as well as district level attributes that vary over time (e.g., local elections), and provide plausibly causal estimates for the effects of temperature on agricultural input use.

5.4.2 Results

The Response of Pesticides Use to Temperature

We estimate equation 5.1 and find that an extra 1 degree day above 8C in the initial growth period (GS1) increases the proportion of households using pesticides by almost 0.3 percentage points (Table 5.1: Column 1). In 2003, almost 30% of maize-farmers in the TAMPA data adopted pesticides. Thus our point estimates imply that an extra 1 DD in GS1 leads to an approximately 1% increase in pesticide users. Similarly, an extra DD in GS1 leads to a 2% increase in the intensity of pesticide use (Table 5.1: Column 2). Note that since pesticide application is most effective - and thus most commonly applied - soon after pests are found on germinated crop, the effect should be most pronounced in GS1, not in pre-planting (PP) or post-planting (GS2) periods. This is precisely what we find.

If greater heat increases the incidence of weeds, we should also observe an increase in manual weeding labor. Indeed, we find that an extra degree day in the pre-planting period (PP) is associated with a 0.017 days (0.2%) increase in own (household) weeding labor per acre (Table 5.1: Column 5). In fact, the effects on weeding labor start during pre-planting (PP), when increased weeding during land preparation would be a natural response to more robust weed growth in warmer weather.[16]

Next, we estimate Equation 5.2 and find that an extra day above 22C relative to a day with average temperature below 18C in the initial growth period (GS1) increases the proportion of households using pesticides by over 1.5 percentage points (Figure 5.4: Panel (a)). Similarly, an extra day above 22C relative to a day below 18C in the initial growth period (GS1) leads to a 12% increase in the intensity of pesticide use (Figure 5.4: Panel (b)). Lastly, an extra day above 22C relative to a day below 18C in the pre-planting period (PP) is associated with a

[16]The effect of an extra degree day over 8C in the initial growth period (GS1) and the post-planting period (GS2) on own weeding effort, however, is quite imprecise. If weed growth is aggressive, farmers might use herbicides - a pesticide targeted specially at weeds in the early post-planting stage (GS1) as a substitute for weeding labor (170). Once the crop is established (GS2), however, any further weed control requires additional labor effort, which continues nearly until harvest. One explanation for the noisy GS2 coefficient might be non-linearities in the effects of temperature on weed growth: (i) we find a statistically significant positive effect of an extra degree day over 21C in GS2 on own weeding labor and (ii) in our nonparametric econometric model, we find large positive effect of temperature on own weeding labor in the post-planting period. Lastly, we find an extra degree day over 8C in the initial vegetative growth phase (GS1) is associated with a 1% increase in expenditure on hired labor per acre (Table D.9). This suggests during the planting period (GS1), presumably facing greater constraints on own labor, farmers tackle aggressive weed growth using herbicides and hired weeding labor.

0.14 day increase in own (household) weeding labor per acre (Figure 5.4: Panel (e)). The effects on weeding labor continues throughout the growing season: although imprecisely estimated, an extra day above 22C relative to a day below 18C in the initial growth period (post-planting period) is associated with a 0.04 (0.07) day increase in own weeding labor per acre.

Combined with the qualitative evidence presented in Table D.7, these results strongly suggest that early growing season temperatures in the pre-planting and initial vegetative growth stages increase the incidence of pests and diseases, driving use of adaptive inputs like pesticides in the early crop growth stages. We find no significant impact of heat during latter stages of the growing season, by which time farmer response to crop diseases and pests is likely unproductive. Effects on weeding labor start early, and are equally pronounced deeper into the growing season as the ability to reverse the adverse effects of weed competition persists longer as well. Household labor can clear weeds manually if they survive initial application of herbicides, or to tackle encroachment of weeds that arise later in the growing season, due to higher than normal temperatures.

The Effects of Temperature on Fertilizer Use

Next, we examine effects on productivity-enhancing inputs like inorganic fertilizer. We find that an extra DD above 8C in the initial planting or basal fertilizer application period (GS1) decreases the proportion of households applying fertilizer by 0.1 percentage points (Table 5.1: Column 3). These effects coincide temporally with the pesticide effects observed, consistent with a liquidity constraint or a production risk mechanism. Almost 65% of the households in our balanced panel applied fertilizer in 1997, so a 0.1 percentage point decrease translates into a 0.15% decrease from adoption levels in Round 1. Similarly, an extra DD over 8C in GS1 reduces fertilizer application rates per acre by around 1.3% (Table 5.1: Column 4). These effects are driven by early growing season temperatures, coinciding with the basal fertilizer application period, by which time financial constraints typically begin to bind, consistent with qualitative evidence presented in Table D.8.

We estimate Equation 5.2 and find that an extra day above 22C relative to a day with average temperature below 18C in the initial growth period (GS1) decreases the proportion of households applying fertilizer by roughly 1 percentage point (Figure 5.4: Panel (c)). Similarly, an extra day above 22C relative to a day below 18C in the initial growth period (GS1) reduces fertilizer application rates per acre by 10% (Figure 5.4: Panel (d)).

Back of the envelope estimates indicate a roughly one-to-one correspondence between increase in defensive expenditures and reduction in expenditure on fertilizer: An extra degree day in the initial planting period (GS1) increases expected pesticide expenditure by KES 4.17, and reduces fertilizer expenditure by KES 12.99. Additionally, an extra degree day in PP increases the cost of own weeding labor (opportunity cost) by KES 9.87.[17][18] This might suggest that as liquidity constraints begin to bind for farmers, expenditure on loss-reducing adaptive inputs necessitates reduction in fertilizer use.

[17] 1 United States Dollar (USD) = 100 Kenyan Shilling (KES).

[18] We compute the average price/kg for both pesticides and inorganic fertilizer using the shilling amount spent by users of each input per acre divided by the kilogram quantity used per acre across rounds. We use the cost of hired weeding labor/day for households who hired weeding labor to impute the cost of own weeding labor/day. On average 52.14 kg/acre of fertilizer is used across rounds, and a kilogram of fertilizer costs KES 24.91 on average. So, using coefficients from Table 5.1, an extra degree day decreases fertilizer expenditure by (0.01*52.14)*24.91. Similarly, pesticide expenditure increased by (0.02*0.43)*484.77, while cost of own weeding labor increased by (0.02*4.88)*101.08.

However, another mechanism might be that increased ex ante maize yield risk, due to an increase in disease, pest, and weed pressure, could adversely affect fertilizer uptake. In Table D.10, we show an extra degree day in the initial vegetative growth stage (GS1) decreases total agricultural input expenditure per acre by 0.9%. The negative and statistically significant point estimate is consistent with the hypothesis that farmers are trading off defensive input expenditures for productive input expenditures but perhaps also responding to changes in output risk due to increase in the incidence of pests, crop diseases, and weeds.

Robustness Checks

We exploit plausibly random round-by-round variation in temperature at the village level beyond time-invariant village level characteristics and time-varying spatial or administrative features, for which we control with province-by-round fixed effects, to provide plausibly causal estimates for the effects of temperature on agricultural input use.[19] After removing village and province-by-round fixed effects, any remaining temperature variation pertains only to within-province-round deviations from village means.

Since Kenyan provinces are large and topographically heterogeneous, it is plausible that we can control for time varying administrative features at a much smaller spatial unit like district, and still have enough variation to precisely estimate our coefficients of interest. However, generally whenever, for example, eastern Migori, a district in Nyanza province, is warmer than normal, so is western Migori, because temperatures vary smoothly in space due to ther-

[19]Including household fixed effects doesn't affect our estimates since the treatment (temperature) is at the village level (Table D.11 and Figure D.6).

modynamics. Therefore, we might not have sufficient identifying variation in temperature after removing household and district-by-year fixed effects to get precise estimates.

We report within- and across-province temperature deviations from province-specific time trends and village means, as well as within-province-round and within-district-round temperature deviations from village means in Table D.12. The entries report the percentage of households-by-round observations with deviations at least as large as 5 or 10 degrees, averaged over the five survey rounds. For example, the "Removed Prov-Specific Time Trends" degree-days column indicates that 65% and 49% of households-by-round observations observed deviations larger than 5 and 10 degree-days in the planting period (GS1), respectively. The corresponding percentages for the "Removed Province*Round Effects" and the "Removed District*Round Effects" degree-days columns are 50% and 21% and 23% and 7%, respectively. Unsurprisingly, an econometric model with province-round fixed effects exploit smaller (greater) residual temperature variation than a specification with province-specific time trends (district-round fixed effects).

In Table D.13 and Figure D.7, we remove province-by-round fixed effects, instead including province-specific linear, quadratic, and cubic time trends to control for province-specific time-variant unobservables. We exploit both within- and across-province temperature deviations from province-specific time trends and village means. Our point estimates remain unaffected.

Next, we estimate Equations 5.1 and 5.2 with district-by-round fixed effects instead of province-by-round effects. We lose precision for pesticide use, although the point estimate remains relatively unaffected (Table D.14 and Figure

D.8).

A sizable proportion of households, across rounds, did not use fertilizer or pesticides. Thus, limited (specifically, censored) dependent variable models might be appropriate for estimating the effect of temperature on intensity of input use. However, fixed effects in tobit models based on the normal distribution yield inconsistent estimates, as fixed effects cannot be treated as incidental parameters without biasing the other model coefficients, so long as N>T (206). Thus, for consistent estimation, we provide regression estimates using the Honoré semi-parametric fixed effect tobit estimator (201).[20]

As before, the effects on pesticide and fertilizer use are driven by early growing season temperatures. Moreover, early growing season estimates are statistically significant as well. We also provide regression estimates for weeding labor. Table D.15 shows the effects of temperature on intensity of pesticide and fertilizer use based on Honoré household fixed effects tobit. For comparison, the standard tobit is also presented in Table D.16. Qualitative conclusions drawn from our main results presented in Table 5.1 remain unchanged with either censored dependent variable estimator.

In Tables D.17 and D.18, we show our results are relatively unaffected when we assign a uniform maize crop calendar across villages in the data. In Table D.19, we adjust standard errors to reflect spatial dependence as modeled in (103), and implemented by (202). We allow errors to be spatially autocorrelated within a distance of 500 km. Our point estimates remain precisely estimated.[21]

[20]We use Honoré's Pantob program, accessible here: http://www.princeton.edu/ honore/stata/

[21]We used 22 unique grid points to generate weather data for villages in our data (Figure D.1). In Table D.20, we cluster our standard errors at the grid point level. In Table D.21, we cluster-bootstrap (22 clusters) our standard errors following (80). Our coefficients of interest remain precisely estimated.

In Tables 5.2 - 5.6 we demonstrate that effects of temperature on agricultural input decisions are robust to the choice of lower bound used to calculate cumulative growing degree days (GDDs).

Next, we employ a sinusoidal interpolation between the daily minimum and maximum temperature (108; 364). We follow (323), and generate growing degree days accounting for within-day temperature variations, not just the daily mean temperature, and estimate the effects on agricultural input response. The core story line remains; the point estimates are qualitatively similar across temperature thresholds (Tables 5.7 - 5.10).

Lastly, we examine the relationship between growing degree days over 8C and agricultural yields amongst maize farmers in the data. Almost 45% of maize-growers in the TAMPA data set indicated that variation in temperature reduced crop yields (Table D.7). Yet the warmer temperatures experienced in these temperate zones should not weaken maize growth physiologically.[22] Farmers' responses therefore most likely reflect the biotic stresses we have emphasized.

To unpack this effect, we estimate a reduced form relationship between temperatures in the growing season and maize yields; that is, we observe the net effect of at least the following channels of impact: an increase in incidence of pests, weeds and crop diseases, consequent increase in pesticide use and manual weeding, decrease in fertilizer use, and an unlikely direct effect of higher temperatures on maize yields. We find that an extra degree day over 8C in the initial growth stage (GS1) reduces maize yields by 0.38% (Table D.22). Next, we

[22]Maize yields only decline above 29-30C (249; 345). The average daily temperatures for villages in our sample are well below 30C (Figure 5.1). In fact, the 99th percentile of the distribution of daily *maximum* temperatures for villages in our sample is 32C (Figure 5.2).

estimate a flexible model of the effects of temperature on maize yields. Relative to the kink point, $T(19C - 20C)^{GS1}_{jdqt}$, we find an extra day below 19C and above 20C in GS1 reduces maize yields, with comparatively model effects of an extra day below 19C and above 20C in PP and GS2 (Figure D.9). Lastly, we account for within-day temperature variations, we find an effect of between -0.6 and -0.9% from the initial planting period temperatures, consistent with our prior results (Table D.23).

In Appendix D.3, we present a lower bound back-of-the-envelope estimate of the value of these within-season adaptations. Defensive investments undertaken by the average maize farmer in response to an extra DD over 8C protected 3.48 kg of maize yield/acre, roughly 75% of expected loss.

Overall, the estimation results are consistent with predictions from the agronomic literature and with farmers qualitative comments, and stand up to various robustness tests.

Hetereogenous Effects by Wealth

Precisely disentangling the effects of credit constraints and ex ante risk falls outside the scope of this paper, especially because we lack good measures of farmer risk aversion or liquidity constraints.[23] We can nonetheless provide suggestive empirical evidence of an association between farmer input response and farmer wealth that suggests plausibly heterogeneous effects of rising temperatures due to farmers' differential ability and willingness to cope with temperature-induced increased incidence of pests and diseases. To examine such a mech-

[23]We would have liked to at least test the liquidity constraints hypothesis by looking for within-season adjustments in other expenditures, but the data set does not include temporally disaggregated (monthly) consumption expenditures, so we are unable to do a test like (48).

anism, the key thought experiment involves the question of whether, ceteris paribus, changes in ex ante income or income risk affect input use. We exploit plausibly exogenous changes in temperature over time across relatively 'poor' and 'wealthy' households under the maintained hypotheses that poor households are more likely to face binding financial liquidity constraints and will be more risk averse for a given increase in biotic risk exposure (i.e., preferences exhibit decreasing absolute risk aversion). We show suggestive evidence that household wealth differences are associated with different responses to higher within-season temperatures, consistent with a story of heterogeneous effects among farmers.

We use baseline (Round 1) land ownership as a proxy for wealth. We separate the balanced sample by terciles, and denote households in the bottom tercile as relatively 'poor'. We then estimate the relationships between heat and agricultural input use, now adding interaction terms between degree days in each phase of the crop cycle (PP, GS1 and GS2), and a 0-1 binary wealth variable which takes value 1 if wealth for household i is in the bottom tercile, that is if the 1996-97 land holding is less than 2.5 acres, 0 otherwise. We find that poorer households are less likely to adapt to higher temperatures via pesticide use. These effects are consistent with the binding liquidity constraints hypothesis, but less so with a risk aversion story if pesticide purchases reduce risk and farmers exhibit constant or decreasing absolute risk aversion.

We also examine the relationship between GDDs and fertilizer use by household wealth. We find that poorer households use less fertilizer in response to higher temperatures. Lastly, we find poorer households engage in fewer own (household) weeding labor days in response to higher temperatures (Tables D.24, D.25, and D.26).[24]

These results suggest that (i) wealthier farmers adapt more through increased pesticide use than their poorer neighbors in response to a temperature-induced increase in incidence of pests, weeds and diseases; (ii) wealthier farmers also reduce their expenditure on fertilizer less in face of higher temperatures. These associations suggest that higher temperatures may lead to regressive distributional yield and income effects within low-income agrarian communities. Limited financial resources thus constrain uptake of loss-reducing inputs and aggravate the reduction in fertilizer application as temperature increases.

5.5 Conclusion

In this paper, we show that farmers in a low-income country can quickly adjust agricultural input use to within-season temperature variation. We find that maize farmers in Kenya increase pesticide use and household weeding labor in response to higher temperatures, and reduce fertilizer use. We present suggestive evidence that these effects are driven by pests, weeds and crop diseases that are sensitive to temperature, and confront farmers with a trade-off. Financially constrained households are induced to reduce spending on productivity-enhancing fertilizer and to increase defensive expenditure on loss-reducing pesticides and on weeding labor.

Yields are the joint product of crop physiological responses to higher temperatures holding input use constant, and the effects of induced changes in

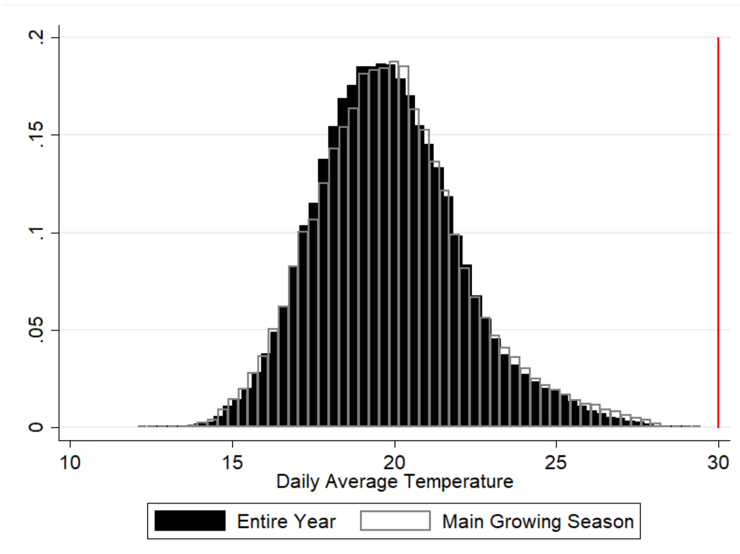
[24] In Tables D.27, D.28, and D.29, We use average land ownership across all five rounds as a proxy for wealth for all rounds. The point estimates remain largely unchanged.

input application patterns on crop yields. Our findings indicate that warmer temperatures, by influencing input application patterns, may affect agricultural production even in regions where temperatures are not high enough to directly adversely affect crop growth. The defensive investments farmers quickly undertake within a growing season in response to temperature-induced biotic stresses affect patterns of uptake of modern agricultural technologies in low-income agrarian communities. Finally, our results suggest that farmer responsiveness is sensitive to the distribution of landholding, and thus wealth, in these communities.

5.6 Tables and Figures

5.6.1 Figures

Figure 5.1: Daily Average Temperature in TAMPA Sample (1990-2012)



Notes: Distribution of average daily temperatures in villages in TAMPA from 1990-2012. According to existing literature, temperature affects maize yields only after 30C, represented by the red line (249; 345).

Figure 5.2: Daily Maximum Temperature in TAMPA Sample (1990-2013)

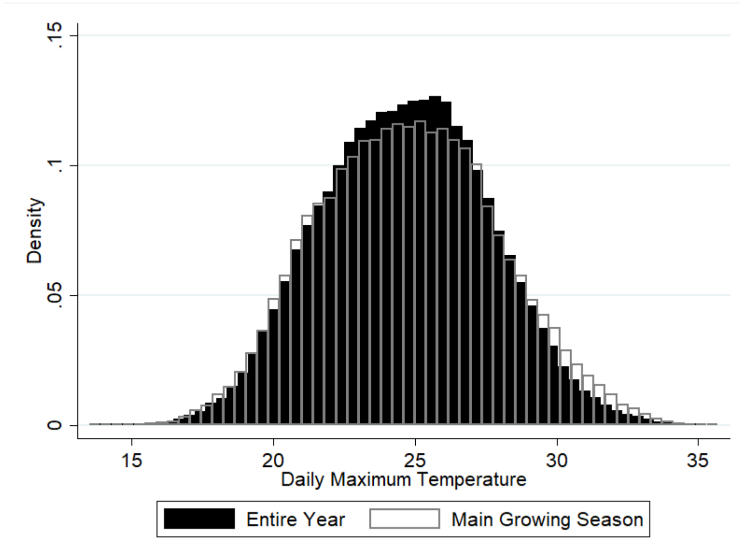
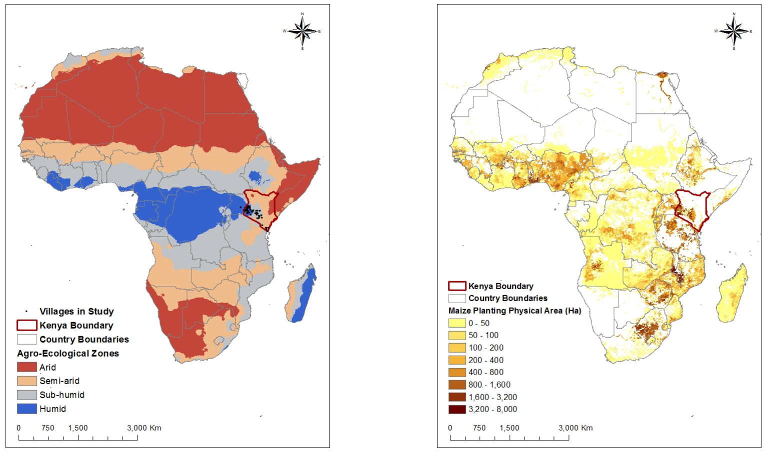


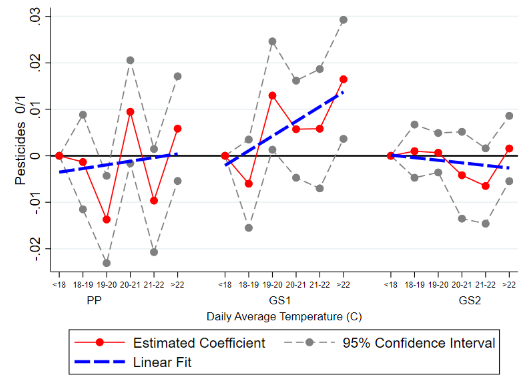
Figure 5.3: Agro-Ecological Zones and Maize Production in Africa



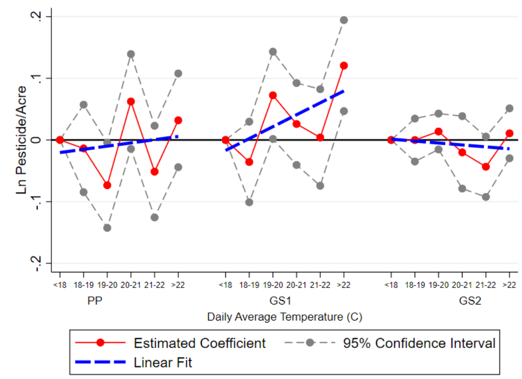
Source: Agro-ecological zones - IFPRI Harvest Choice (www.harvestchoice.org.); Maize Production in Africa: Spatial Production Allocation Model (SPAM), 2005 (www.mapSPAM.info)

Agro-Ecological Zones (AEZs): Agro-ecological zones (AEZs) are geographical areas sharing similar climate characteristics (e.g., rainfall and temperature) with respect to their potential to support (usually rain-fed) agricultural production. Because of the general similarity of production conditions, many agricultural technologies, practices and production systems tend to behave or respond consistently within a specific AEZ. AEZs therefore provide a useful spatial framework for identifying the potential area extent of applicability of given innovations and, futhermore, the likely potential for production related innovations to "spillover" from one country (or continent) to another. AEZs provide an ecology-based division of geographic space as opposed to administrative or political boundaries within which environmental conditions could vary significantly. The tabulation of rural population by AEZ for Sub-Saharan Africa indicates that almost 23% of the rural population lives in more humid highland regions.

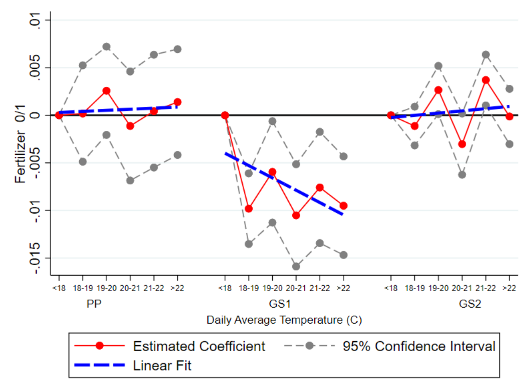
Figure 5.4: Temperature Bins: Temperature, Fertilizer and Pesticide Use



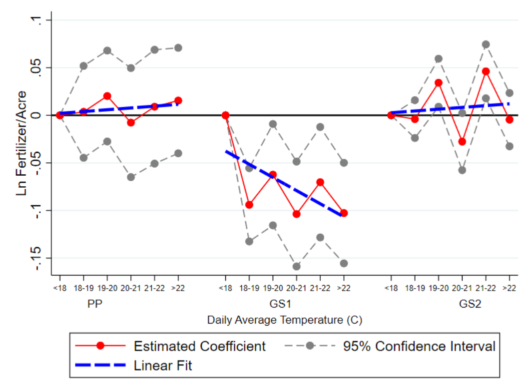
(a) Pesticides 0/1



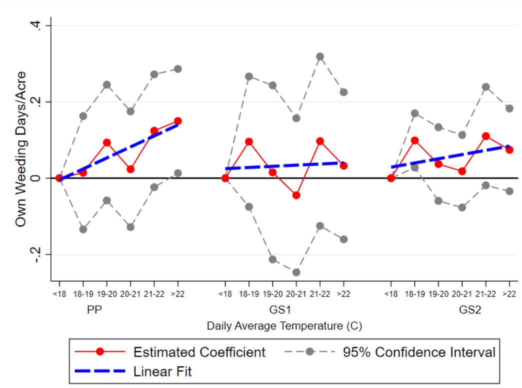
(b) Ln Pesticide/Acre



(c) Fertilizer 0/1



(d) Ln Fertilizer/Acre



(e) Own Weeding Days/Acre

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use and 3 survey rounds (2003-04, 2006-07 and 2009-10) for pesticides and weeding labor days. The figure presents the effects of temperature (captured via number of days in each temperature bin) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. All figures include village and province-by-year fixed effects as well as controls for precipitation. Standard errors are clustered by village.

5.6.2 Tables

Table 5.1: Temperature, Fertilizer and Pesticide Use

	(1) Pesticides 0/1 β / SE	(2) Ln Pesticide/Acre β / SE	(3) Fertilizer 0/1 β / SE	(4) Ln Fertilizer/Acre β / SE	(5) Own Weeding Days/Acre β / SE
CY PP DD >8C	0.0010	0.0067	-0.0004	-0.0044	0.0171**
	(0.0008)	(0.0058)	(0.0004)	(0.0042)	(0.0086)
CY GS1 DD >8C	0.0027***	0.0214***	-0.0013**	-0.0131**	-0.0068
	(0.0009)	(0.0058)	(0.0005)	(0.0050)	(0.0117)
CY GS2 DD >8C	-0.0005	-0.0022	-0.0000	0.0005	0.0049
	(0.0004)	(0.0029)	(0.0002)	(0.0019)	(0.0062)
Village FE	Yes	Yes	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Observations	3726	3726	6210	6210	3726
R^2	0.336	0.353	0.594	0.657	0.164

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use and 3 survey rounds (2003-04, 2006-07 and 2009-10) for pesticides and weeding labor days. The table presents the effects of temperature (captured via degree days (DD) over 8C) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 5.2: Alternative GDD Lower Bounds: Temperature and Pesticide Use (0/1)

	(1) Pesticides 0/1 β / SE	(2) Pesticides 0/1 β / SE	(3) Pesticides 0/1 β / SE	(4) Pesticides 0/1 β / SE
CY PP DD >18C	0.0013			
	(0.0010)			
CY GS1 DD >18C	0.0028***			
	(0.0010)			
CY GS2 DD >18C	-0.0005			
	(0.0005)			
CY PP DD >19C		0.0015		
		(0.0010)		
CY GS1 DD >19C		0.0029**		
		(0.0011)		
CY GS2 DD >19C		-0.0006		
		(0.0006)		
CY PP DD >20C			0.0017	
			(0.0012)	
CY GS1 DD >20C			0.0034**	
			(0.0016)	
CY GS2 DD >20C			-0.0007	
			(0.0008)	
CY PP DD >21C				0.0019
				(0.0014)
CY GS1 DD >21C				0.0063**
				(0.0026)
CY GS2 DD >21C				-0.0004
				(0.0015)
Village FE	Yes	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes	Yes
Observations	3726	3726	3726	3726
R^2	0.336	0.336	0.336	0.336

Notes: Sample includes 1242 households balanced over 3 survey rounds (2003-04, 2006-07 and 2009-10). The table presents the effects of temperature (captured via degree days (DD)) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village. *Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 5.3: Alternative GDD Lower Bounds: Temperature and Pesticide Use (kg/acre)

	(1) Ln Pesticide/Acre β / SE	(2) Ln Pesticide/Acre β / SE	(3) Ln Pesticide/Acre β / SE	(4) Ln Pesticide/Acre β / SE
CY PP DD >18C	0.0081			
	(0.0066)			
CY GS1 DD >18C	0.0229***			
	(0.0064)			
CY GS2 DD >18C	-0.0025			
	(0.0036)			
CY PP DD >19C		0.0084		
		(0.0071)		
CY GS1 DD >19C		0.0236***		
		(0.0072)		
CY GS2 DD >19C		-0.0042		
		(0.0043)		
CY PP DD >20C			0.0088	
			(0.0079)	
CY GS1 DD >20C			0.0285***	
			(0.0104)	
CY GS2 DD >20C			-0.0064	
			(0.0052)	
CY PP DD >21C				0.0084
				(0.0090)
CY GS1 DD >21C				0.0450***
				(0.0159)
CY GS2 DD >21C				-0.0108
				(0.0079)
Village FE	Yes	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes	Yes
Observations	3726	3726	3726	3726
R^2	0.353	0.353	0.353	0.354

Notes: Sample includes 1242 households balanced over 3 survey rounds (2003-04, 2006-07 and 2009-10). The table presents the effects of temperature (captured via degree days (DD)) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village. *Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 5.4: Alternative GDD Lower Bounds: Temperature and Fertilizer Use (0/1)

	(1) Fertilizer 0/1 β / SE	(2) Fertilizer 0/1 β / SE	(3) Fertilizer 0/1 β / SE	(4) Fertilizer 0/1 β / SE
CY PP DD >18C	-0.0003			
	(0.0004)			
CY GS1 DD >18C	-0.0014**			
	(0.0005)			
CY GS2 DD >18C	0.0001			
	(0.0002)			
CY PP DD >19C		-0.0004		
		(0.0004)		
CY GS1 DD >19C		-0.0014**		
		(0.0006)		
CY GS2 DD >19C		-0.0000		
		(0.0003)		
CY PP DD >20C			-0.0004	
			(0.0005)	
CY GS1 DD >20C			-0.0016**	
			(0.0007)	
CY GS2 DD >20C			0.0001	
			(0.0004)	
CY PP DD >21C				-0.0003
				(0.0005)
CY GS1 DD >21C				-0.0018**
				(0.0008)
CY GS2 DD >21C				0.0003
				(0.0004)
Village FE	Yes	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes	Yes
Observations	6210	6210	6210	6210
R^2	0.594	0.594	0.594	0.594

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10). The table presents the effects of temperature (captured via degree days (DD)) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 5.5: Alternative GDD Lower Bounds: Temperature and Fertilizer Use (kg/acre)

	(1) Ln Fertilizer/Acre β / SE	(2) Ln Fertilizer/Acre β / SE	(3) Ln Fertilizer/Acre β / SE	(4) Ln Fertilizer/Acre β / SE
CY PP DD >18C	-0.0044			
	(0.0043)			
CY GS1 DD >18C	-0.0130**			
	(0.0055)			
CY GS2 DD >18C	0.0005			
	(0.0025)			
CY PP DD >19C		-0.0051		
		(0.0045)		
CY GS1 DD >19C		-0.0132**		
		(0.0059)		
CY GS2 DD >19C		-0.0009		
		(0.0029)		
CY PP DD >20C			-0.0053	
			(0.0048)	
CY GS1 DD >20C			-0.0160**	
			(0.0072)	
CY GS2 DD >20C			-0.0008	
			(0.0038)	
CY PP DD >21C				-0.0054
				(0.0055)
CY GS1 DD >21C				-0.0180**
				(0.0087)
CY GS2 DD >21C				0.0005
				(0.0044)
Village FE	Yes	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes	Yes
Observations	6210	6210	6210	6210
R^2	0.657	0.656	0.656	0.656

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10). The table presents the effects of temperature (captured via degree days (DD)) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 5.6: Alternative GDD Lower Bounds: Temperature and Own (Household) Weeding Labor Days

	(1) Own Weeding Days/Acre β / SE	(2) Own Weeding Days/Acre β / SE	(3) Own Weeding Days/Acre β / SE	(4) Own Weeding Days/Acre β / SE
CY PP DD >18C	0.0166*			
	(0.0093)			
CY GS1 DD >18C	-0.0072			
	(0.0128)			
CY GS2 DD >18C	0.0041			
	(0.0066)			
CY PP DD >19C		0.0184*		
		(0.0105)		
CY GS1 DD >19C		-0.0058		
		(0.0140)		
CY GS2 DD >19C		0.0047		
		(0.0083)		
CY PP DD >20C			0.0236*	
			(0.0125)	
CY GS1 DD >20C			0.0145	
			(0.0194)	
CY GS2 DD >20C			0.0159	
			(0.0125)	
CY PP DD >21C				0.0323**
				(0.0149)
CY GS1 DD >21C				0.0375
				(0.0271)
CY GS2 DD >21C				0.0392*
				(0.0219)
Village FE	Yes	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes	Yes
Observations	3726	3726	3726	3726
R^2	0.164	0.164	0.164	0.165

Notes: Sample includes 1242 households balanced over 3 survey rounds (2003-04, 2006-07 and 2009-10). The table presents the effects of temperature (captured via degree days (DD)) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 5.7: Accounting for Within-Day Temperature Variation: Temperature and Pesticide Use (0/1)

	(1) Pesticides 0/1 β / SE	(2) Pesticides 0/1 β / SE	(3) Pesticides 0/1 β / SE	(4) Pesticides 0/1 β / SE	(5) Pesticides 0/1 β / SE
CY PP DD >21C II	0.0017				
	(0.0012)				
CY GS1 DD >21C II	0.0017				
	(0.0014)				
CY GS2 DD >21C II	-0.0011				
	(0.0008)				
CY PP DD >22C II		0.0021*			
		(0.0012)			
CY GS1 DD >22C II		0.0019			
		(0.0018)			
CY GS2 DD >22C II		-0.0009			
		(0.0010)			
CY PP DD >23C II			0.0023		
			(0.0017)		
CY GS1 DD >23C II			0.0048***		
			(0.0015)		
CY GS2 DD >23C II			-0.0010		
			(0.0013)		
CY PP DD >24C II				0.0027	
				(0.0022)	
CY GS1 DD >24C II				0.0067**	
				(0.0028)	
CY GS2 DD >24C II				-0.0011	
				(0.0018)	
CY PP DD >25C II					0.0039
					(0.0027)
CY GS1 DD >25C II					0.0100**
					(0.0039)
CY GS2 DD >25C II					-0.0008
					(0.0024)
Village FE	Yes	Yes	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Observations	3726	3726	3726	3726	3726
R^2	0.335	0.335	0.336	0.336	0.336

Notes: Sample includes 1242 households balanced over 3 survey rounds (2003-04, 2006-07 and 2009-10). The table presents the effects of temperature (captured via degree days (DD)) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village. *Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 5.8: Accounting for Within-Day Temperature Variation: Temperature and Pesticide Use (kg/acre)

	(1) Ln Pesticide/Acre β / SE	(2) Ln Pesticide/Acre β / SE	(3) Ln Pesticide/Acre β / SE	(4) Ln Pesticide/Acre β / SE	(5) Ln Pesticide/Acre β / SE
CY PP DD >21C II	0.0096				
	(0.0078)				
CY GS1 DD >21C II	0.0215***				
	(0.0082)				
CY GS2 DD >21C II	-0.0054				
	(0.0060)				
CY PP DD >22C II		0.0103			
		(0.0080)			
CY GS1 DD >22C II		0.0225**			
		(0.0103)			
CY GS2 DD >22C II		-0.0050			
		(0.0079)			
CY PP DD >23C II			0.0126		
			(0.0114)		
CY GS1 DD >23C II			0.0389***		
			(0.0095)		
CY GS2 DD >23C II			-0.0059		
			(0.0099)		
CY PP DD >24C II				0.0163	
				(0.0144)	
CY GS1 DD >24C II				0.0495***	
				(0.0172)	
CY GS2 DD >24C II				-0.0090	
				(0.0122)	
CY PP DD >25C II					0.0216
					(0.0181)
CY GS1 DD >25C II					0.0680***
					(0.0241)
CY GS2 DD >25C II					-0.0137
					(0.0156)
Village FE	Yes	Yes	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Observations	3726	3726	3726	3726	3726
R^2	0.352	0.352	0.354	0.352	0.352

Notes: Sample includes 1242 households balanced over 3 survey rounds (2003-04, 2006-07 and 2009-10). The table presents the effects of temperature (captured via degree days (DD)) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village. *Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 5.9: Accounting for Within-Day Temperature Variation: Temperature and Fertilizer Use (0/1)

	(1) Fertilizer 0/1 β / SE	(2) Fertilizer 0/1 β / SE	(3) Fertilizer 0/1 β / SE	(4) Fertilizer 0/1 β / SE	(5) Fertilizer 0/1 β / SE
CY PP DD >21C II	-0.0008				
	(0.0006)				
CY GS1 DD >21C II	-0.0022***				
	(0.0008)				
CY GS2 DD >21C II	0.0001				
	(0.0004)				
CY PP DD >22C II		-0.0004			
		(0.0006)			
CY GS1 DD >22C II		-0.0020**			
		(0.0008)			
CY GS2 DD >22C II		0.0004			
		(0.0006)			
CY PP DD >23C II			-0.0009		
			(0.0008)		
CY GS1 DD >23C II			-0.0023**		
			(0.0011)		
CY GS2 DD >23C II			0.0002		
			(0.0007)		
CY PP DD >24C II				-0.0013	
				(0.0009)	
CY GS1 DD >24C II				-0.0043***	
				(0.0014)	
CY GS2 DD >24C II				0.0000	
				(0.0010)	
CY PP DD >25C II					-0.0015
					(0.0012)
CY GS1 DD >25C II					-0.0052***
					(0.0018)
CY GS2 DD >25C II					-0.0000
					(0.0013)
Village FE	Yes	Yes	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Observations	6210	6210	6210	6210	6210
R^2	0.595	0.594	0.594	0.595	0.595

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10). The table presents the effects of temperature (captured via degree days (DD)) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 5.10: Accounting for Within-Day Temperature Variation: Temperature and Fertilizer Use (kg/acre)

	(1) Ln Fertilizer/Acre β / SE	(2) Ln Fertilizer/Acre β / SE	(3) Ln Fertilizer/Acre β / SE	(4) Ln Fertilizer/Acre β / SE	(5) Ln Fertilizer/Acre β / SE
CY PP DD >21C II	-0.0093				
	(0.0059)				
CY GS1 DD >21C II	-0.0213***				
	(0.0074)				
CY GS2 DD >21C II	0.0016				
	(0.0045)				
CY PP DD >22C II		-0.0056			
		(0.0059)			
CY GS1 DD >22C II		-0.0193**			
		(0.0083)			
CY GS2 DD >22C II		0.0041			
		(0.0059)			
CY PP DD >23C II			-0.0103		
			(0.0077)		
CY GS1 DD >23C II			-0.0231**		
			(0.0099)		
CY GS2 DD >23C II			0.0016		
			(0.0075)		
CY PP DD >24C II				-0.0129	
				(0.0091)	
CY GS1 DD >24C II				-0.0402***	
				(0.0138)	
CY GS2 DD >24C II				0.0003	
				(0.0104)	
CY PP DD >25C II					-0.0146
					(0.0109)
CY GS1 DD >25C II					-0.0461**
					(0.0178)
CY GS2 DD >25C II					-0.0014
					(0.0135)
Village FE	Yes	Yes	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Observations	6210	6210	6210	6210	6210
R^2	0.657	0.657	0.657	0.657	0.657

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10). The table presents the effects of temperature (captured via degree days (DD)) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 5.11: Accounting for Within-Day Temperature Variation: Temperature and Own (Household) Weeding Labor Days

	(1)	(2)	(3)	(4)	(5)
	Own Weeding Days/Acre	Own Weeding Days/Acre	Own Weeding Days/Acre	Own Weeding Days/Acre	Own Weeding Days/Acre
	β / SE	β / SE	β / SE	β / SE	β / SE
CY PP DD >21C II	0.0264**				
	(0.0122)				
CY GS1 DD >21C II	-0.0192				
	(0.0145)				
CY GS2 DD >21C II	0.0080				
	(0.0111)				
CY PP DD >22C II		0.0284**			
		(0.0123)			
CY GS1 DD >22C II		-0.0215			
		(0.0140)			
CY GS2 DD >22C II		0.0064			
		(0.0131)			
CY PP DD >23C II			0.0350*		
			(0.0184)		
CY GS1 DD >23C II			-0.0141		
			(0.0232)		
CY GS2 DD >23C II			0.0106		
			(0.0161)		
CY PP DD >24C II				0.0391*	
				(0.0234)	
CY GS1 DD >24C II				-0.0044	
				(0.0361)	
CY GS2 DD >24C II				0.0210	
				(0.0206)	
CY PP DD >25C II					0.0500*
					(0.0290)
CY GS1 DD >25C II					0.0095
					(0.0483)
CY GS2 DD >25C II					0.0428
					(0.0295)
Village FE	Yes	Yes	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Observations	3726	3726	3726	3726	3726
R^2	0.164	0.164	0.164	0.164	0.164

Notes: Sample includes 1242 households balanced over 3 survey rounds (2003-04, 2006-07 and 2009-10). The table presents the effects of temperature (captured via degree days (DD)) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Appendix A

Chapter 1 of appendix

A.1 Details of the Model

In our text we sketch an outline of a model that generates testable hypotheses for how public colleges may affect the market for lower levels of schooling. Here we present the details of the model.

A.1.1 The Supply of Schools

Private schools maximize profit, where profits are π_j for school j. In the text, we define total educational output (in student-years) as $Q_j = \overline{\theta}X_j$ and cost function $Z(X_j) = z_{1j}X_j + \frac{1}{2}z_2X_j^2$ to be quadratic. z_{1j} reflects the heterogeneity in costs across schools and districts, drawn from the distribution $G(z_{1j})$, where some schools use their inputs more effectively than others. This distribution varies across districts as it may be cheaper to hire teachers in some districts, and others may have better public infrastructure, like electricity or drinking water.

$$\pi_j = Q_j p - Z(X_j) = p\bar{\theta}X_j - Z(X_j)$$

This implies $X_j^* = \dfrac{p\bar{\theta} - z_{1j}}{z_2}$, output is $Q_j^* = \bar{\theta}\dfrac{p\bar{\theta} - z_{1j}}{z_2}$, and $\pi_j^* = \frac{(p\bar{\theta}-z_{1j})^2}{2z_2}$.

The total number of potential private schools is N. School j would enter only if its profit is positive, and cost z_{1j} is drawn from $G(z_{1j})$. The fraction of schools in the district is $G(p\bar{\theta})$, and the number of private schools in the district that enter is[1]

$$N_1 = N\int_0^{p\bar{\theta}} z_{1j}\,\mathrm{d}G(z_{1j}) = p\bar{\theta}N$$

Given this, the total supply of schooling in the district is

$$Q_{Sy} = \sum_{j=1}^{N_1} Q_j = \sum_{j=1}^{N_1} \bar{\theta}\frac{p\bar{\theta} - z_{1j}}{z_2} = \frac{p\bar{\theta}^2 N}{z_2}(p\bar{\theta} - \overline{z_1}) \tag{A.1}$$

A.1.2 Demand for Schooling and School Choice

Demand for schooling depends on the costs of going to school and the returns to schooling. The cost for child i to attend school j is

$$c_{ij} = \alpha p_k + \beta T_{ij} - \gamma ln(W_i) - \Delta_i\ , \tag{A.2}$$

where the costs depend on tuition p_k, travel costs T_{ij}, wealth W_i and ability Δ_i. Tuition is $p_k = 0$ for public schools and $p_k = p$ for private schools, where $p > 0$. Increases in wealth makes schooling more affordable, also allowing us to capture any consumption value of education. Household wealth W_i, travel costs

[1] Note that there is no uncertainty in costs, so no expectations operator.

T_{ij} and abilities Δ_i are drawn from distributions such that their means ($ln(w)$, δ and T_k) vary across districts:

$$ln(W_i) = ln(w) + \zeta_i \quad \& \quad \Delta_i = \delta + \delta_i \quad \& \quad T_{ij} = T_k + \eta_{ij} \quad for \ \{k = s, p\}$$

For ease of notation, we define an error term ε_{ij} based on these costs, and restate c_{ij}:

$$\varepsilon_{ij} \equiv \beta\eta_{ij} - \gamma\zeta_i - \delta_i \quad \& \quad c_{ij} = \alpha p_k + \beta T_k - \gamma ln(w) - \delta + \varepsilon_{ij} \quad for \ \{k = s, p\}$$

Children will attend school if the returns to education, r, are greater than the costs. If a child decides to attend, school choice only depends on cost. The lowest-cost school J is chosen (as captured by the *min* operator). A child attends if:

$$q_i \equiv 1(r - min(c_{ij}) > 0) = 1(r - min(\alpha p_k + \beta T_k - \varepsilon_{ij}) + \gamma ln(w) + \delta > 0) \ , \qquad \text{(A.3)}$$

where the returns to education r for both public and private schools are equal.[2]

The probability of a student going to school k depends on whether school k is public or private. There are N_0 public schools, N_1 private schools, and M students. If the costs ε_{ij} is i.i.d. with distribution F(.), the aggregate demand for private school is[3]

$$Q_d = MN_1F(\phi - \alpha p)[1 - F(\phi)]^{N_0}[1 - F(\phi - \alpha p)]^{N_1-1} \ , \qquad \text{(A.4)}$$

[2]Theoretically, the returns to schooling can be allowed to be different between private and public schools, without a change in our comparative statics. Given that (281), find similar test scores for subjects commonly taught in both schools, we model them to be the same.

[3]Note that we do not need to derive the demand for each particular private school separately, just the aggregate demand for private schools.

where $\phi \equiv r - \beta T_k + \gamma ln(w) + \delta$. Notice from the supply-side $N_1 = Np\overline{\theta}$. In equilibrium the supply and demand of private schooling are equal. From Equations A.1 and A.4 we get:

$$MN_1F(\phi - \alpha p)[1 - F(\phi)]^{N_0}[1 - F(\phi - \alpha p)]^{N_1 - 1} = \frac{N_1\overline{\theta}}{z_2}(p\overline{\theta} - \overline{z_1}) \qquad \text{(A.5)}$$

A.1.3 Comparative Statics Details

From Equation A.5 we derive the equilibrium condition for the market for education. In order to solve for a closed form solution and do comparative statics we specify the error term distribution $F(.)$ to be child and school specific of Type I Extreme Value. The probability with which a student chooses a private school from the menu of J schools is

$$= \frac{exp(r - \alpha p - \beta T_p + \gamma ln(w) + \delta)}{\sum^{J} exp(r - \alpha p - \beta T_k + \gamma ln(w) + \delta)}$$

$$= \frac{exp(r - \alpha p - \beta T_p + \gamma ln(w) + \delta)}{Np\overline{\theta}exp(r - \alpha p - \beta T_p + \gamma ln(w) + \delta) + N_0exp(r - \beta T_s + \gamma ln(w) + \delta) + 1} \qquad \text{(A.6)}$$

$$Q_d = \frac{MNp\overline{\theta}exp(r - \alpha p - \beta T_p + \gamma ln(w) + \delta)}{Np\overline{\theta}exp(r - \alpha p - \beta T_p + \gamma ln(w) + \delta) + N_0exp(r - \beta T_s + \gamma ln(w) + \delta) + 1} \qquad \text{(A.7)}$$

$$Or \quad Q_d = \frac{MNp\overline{\theta}}{Np\overline{\theta} + N_0exp(\alpha p + \beta(T_p - T_s)) + exp(\alpha p + \beta T_p - \gamma ln(w) - \delta - r)} \qquad \text{(A.8)}$$

Plugging in this value of Q_d in A.5 we get With M students, summed over all $Np\overline{\theta}$ private schools, from Equation A.5 we get

$$\frac{M}{Np\overline{\theta} + N_0exp(\alpha p + \beta(T_p - T_s)) + exp(\alpha p + \beta T_p - \gamma ln(w) - \delta - r)} = \frac{\overline{\theta}}{z_2}(p\overline{\theta} - \overline{z_1}) \tag{A.9}$$

After equating private school supply with demand, we derive the following equation:

$$\frac{M}{\Lambda} - \frac{\overline{\theta}}{z_2}(p\overline{\theta} - \overline{z_1}) = 0 \ \ , \tag{A.10}$$

where $\Lambda \equiv Np\overline{\theta} + N_0exp(\alpha p + \beta(T_p - T_s)) + \lambda$, and also $\lambda \equiv exp(\alpha p + \beta T_p - \gamma ln(w) - \delta - r)$.

Using this, we can derive the following using the implicit function theorem:

1. $\frac{dp}{dln(w)} = -\frac{-\left(N\overline{\theta}+N_0exp(\alpha p+\beta(T_p-T_s))\alpha+\lambda\alpha+\Lambda^2\overline{\theta}^2 z_2^{-1}\right)}{\lambda\gamma} > 0$ and $\frac{dN_1}{dln(w)} = N\overline{\theta}\frac{dp}{dln(w)} > 0$
2. $\frac{dQ_d}{dT_p} = -\frac{MNp\overline{\theta}\lambda\beta}{\Lambda^2} < 0$
3. $\frac{dQ_d}{dT_p} = -\frac{MNp\overline{\theta}\lambda(-\beta)}{\Lambda^2} < 0$
4. $\frac{dp}{d\delta} = -\frac{-\left(N\overline{\theta}+N_0exp(\alpha p+\beta(T_p-T_s))\alpha+\lambda\alpha+\Lambda^2\overline{\theta}^2 z_2^{-1}\right)}{\lambda} > 0$ and $\frac{dN_1}{d\delta} = N\overline{\theta}\frac{dp}{d\delta} > 0$
5. $\frac{dp}{dr} = -\frac{-\left(N\overline{\theta}+N_0exp(\alpha p+\beta(T_p-T_s))\alpha+\lambda\alpha+\Lambda^2\overline{\theta}^2 z_2^{-1}\right)}{\lambda} > 0$ and $\frac{dN_1}{dr} = N\overline{\theta}\frac{dp}{d\delta} > 0$
6. $\frac{dp}{d\overline{\theta}} = -\frac{-\left(N\overline{\theta}+N_0exp(\alpha p+\beta(T_p-T_s))\alpha+\lambda\alpha+\Lambda^2\overline{\theta}^2 z_2^{-1}\right)}{Np-2p\Lambda^2\overline{\theta}M^{-1}z_2^{-1}} > 0$ and $\frac{dN_1}{d\overline{\theta}} = N\overline{\theta}\frac{dp}{d\delta} > 0$
7. $\frac{dp}{dM} = -\frac{-M\left(N\overline{\theta}+N_0exp(\alpha p+\beta(T_p-T_s))\alpha+\lambda\alpha+\Lambda^2\overline{\theta}^2 z_2^{-1}\right)}{\Lambda} > 0$ and $\frac{dN_1}{dM} = N\overline{\theta}\frac{dp}{dM} > 0$
8. $\frac{dp}{dT_s} = -\frac{-\left(N\overline{\theta}+N_0exp(\alpha p+\beta(T_p-T_s))\alpha+\lambda\alpha+\Lambda^2\overline{\theta}^2 z_2^{-1}\right)}{-(-\beta N_0exp(\alpha p+\beta(T_p-T_s))} > 0$ and $\frac{dN_1}{dT_s} = N\overline{\theta}\frac{dp}{dT_s} > 0$
9. $\frac{dp}{d\overline{z_1}} = -\frac{-M\left(N\overline{\theta}+N_0exp(\alpha p+\beta(T_p-T_s))\alpha+\lambda\alpha+\Lambda^2\overline{\theta}^2 z_2^{-1}\right)}{\Lambda^2\overline{\theta}z_2^{-1}} > 0$ and $\frac{dQ_{sy}}{d\overline{z_1}}|_p = -\frac{p\overline{\theta}^2 N}{z_2} < 0$

$\frac{d\frac{dQ_{sy}}{d\overline{z_1}}|_p}{dT_s} = -\frac{\overline{\theta}^2 N}{z_2}\frac{dp}{dT_s} < 0$

10. $\frac{dp}{dz_2} = -\frac{-M\left(N\bar{\theta}+N_0 exp(\alpha p+\beta(T_p-T_s))\alpha+\lambda\alpha+\Lambda^2\bar{\theta}^2 z_2^{-1}\right)}{\Lambda^2\left(p\bar{\theta}^2-\overline{z_1}\right)z_2^{-2}} > 0$ & $\frac{dQ_{sy}}{dz_2}|_p = -\frac{p\bar{\theta}^2 N(p\bar{\theta}-\overline{z_1})}{z_2^2} < 0$

A.2 Benefit Analysis

We use our results to get an estimate of the 'unintended' benefits of elite public colleges, accrued through effects on markets for primary, secondary or higher education, as a proportion of direct or intended benefits of higher education investments, accrued through the training of undergraduate and graduate students. We focus only on unintended benefits accrued education markets in the form of private gains, and ignore other potential benefits like infrastructure upgrades. The estimates obtained through this exercise involve tremendous uncertainty (261). Nonetheless, we believe that these estimates will provide some insight into (hitherto) unaccounted benefits of these elite public colleges.

We begin by estimating the direct or intended benefits of an elite public college imparting higher education. We obtain the enrollment numbers from websites of elite colleges set-up between 2004-2014. We find that the average enrollment is around 800 students. This figure includes undergraduates, masters and PhD students. To get an estimate of the benefit accrued through training these students, we rely on median starting-salaries of students obtained through a survey of 70 companies.[4] Average starting-salaries were summarized by college tiers, with students from Tier 1 students averaging INR 1,305,625; Tier 2, INR 641,812.5; Tier 3, INR 407,375. We estimate direct benefits as the value

[4] Willis Tower Watson, a global advisory company, in (420), polled 70 of Indias top organizations and HR leaders across sectors to gauge campus hiring trends and differentiation of compensation philosophy across college tiers for the following degrees BTech, MTech, MBA and Other Graduates (BA, BCom, BSc and BBA).

added through attending an elite public college. We come up with two annual estimates:

$$LowerBound/College : 800 * (1,305,625 - 641,812.5) = INR\ \ 531,050,000$$

$$UpperBound/College : 800 * (1,305,625 - 407,375) = INR\ \ 718,600,000$$

Next, we estimate indirect, or unintended benefits accrued through the primary and secondary education markets. First, we estimate the benefits accrued to the social planner due to transfers from public to private schools. (281), find that although there exists little difference in output, private schools are more costs effective than public schools. They also provide us with estimates for 'Annual Cost/Child' for both public and private schools in the state of Andhra Pradesh, in India; the per child difference in cost is INR 6,541.12.[5] We calculate the number of rural children, aged 5-16, in private schools in an average treatment districts. Using population numbers from the 2011 census (310,816) and proportion of children in private schools at $\tau = -1$, or 'pre-treatment' (27 percent), we come up with an estimate of 83,920 children. Because the magnitude of decrease in public school enrollment is close to the magnitude of increase in private school enrollment, to estimate annual benefits accrued through transfers, we use coefficients estimating the impact of elite public colleges on private enrollment, at $\tau = 0$ (25 percent) and $\tau = 2$ (40 percent):

$$LowerBound : 310,816 * 0.27 * 0.25 * 6,541.12$$

[5] It is important to note that these figures pertain to the cost incurred by schools, and not household costs. We are not concerned about household costs, since, as per our model children switch from public to private schools only if the cost of attending private schools < cost of attending public schools.

$$UpperBound : 310,816 * 0.27 * 0.40 * 6,541.12$$

Next, we estimate benefits due to increase in educational attainment amongst primary and secondary students. Our NSS estimates suggest that elite public colleges increased educational attainment by 0.3 years, amongst students aged 6-20. The literature on returns to education suggests that an extra year of schooling in India leads to gains ranging from INR 2,000 to 4,000.[6] Thus, we use the 2011 Census to get the number of rural children between ages 6-20 in an average treatment district 307,726, and provide two annual estimates for private gains due to increase in educational attainment:

$$LowerBound : 307,726 * 0.33 * 2,038.40$$

$$UpperBound : 307,726 * 0.33 * 3,902.08$$

Finally, we present total annual indirect benefits per college:

$$LowerBound : INR \;\; 344,231,884.8$$

$$UpperBound : INR \;\; 615,827,738.5$$

Therefore, annual unintended or indirect benefits are anywhere between 48 to 115 percent of the intended or direct benefits of elite public colleges.[7]

[6] Authors' calculations based on (231), INR 3086.72; (229), INR 3902.08; (311), INR 2038.4

[7] We also do year-by-year calculations, for 25 years, where direct benefits, and private gains due to increase in educational attainment only accrue from the fourth year. Furthermore, we estimate cost-savings from transfers using the coefficient at $\tau = 0$, 25 percent, initially, and the coefficient at $\tau = 2$, 40 percent from the third year of elite public colleges. Finally, we discount all future estimates at 5 percent, increase future returns to education, and starting-salaries at elite colleges by 7 percent (growth rate in India). The annual estimates reached through this exercise are very close to the estimates presented above.

A.3 Additional Data Sets

A.3.1 Census Village Directories

We use data from the village census directories in 1991, 2001, and 2011 to procure information on village level infrastructure indicators like access to electricity, roads and tap water. We code electricity access as "1" if electric power was available for all users in the village,"0" otherwise. We code road access as "1" if the village can be accessed through a permanent or paved road, "0" otherwise. Finally, we code tap water as "1" if untreated or treated tap water is available within the village, "0" otherwise. In the 2011 wave, these directories also contain information on presence of private schools and colleges.

A.3.2 Village Night Lights

We use nighttime lights as measured by satellite imagery to capture intensity of changes in electrification within a village. Existing work on India has shown that nighttime lights can be used to detect electrification ((273; 274; 275)). In fact, (92) finds a direct relationship between nighttime lights and electric power consumption in India, and most recently, (75) have used changes in nighttime brightness as an indicator of electrification in India to evaluate the effects of a rural electrification program on electricity access at the village level.

Researchers at the National Oceanic and Atmospheric Administration's (NOAA) National Geophysical Data Center (NGDC) process data from weather satellites that circle the Earth 14 times a day and take pictures between 2030 and

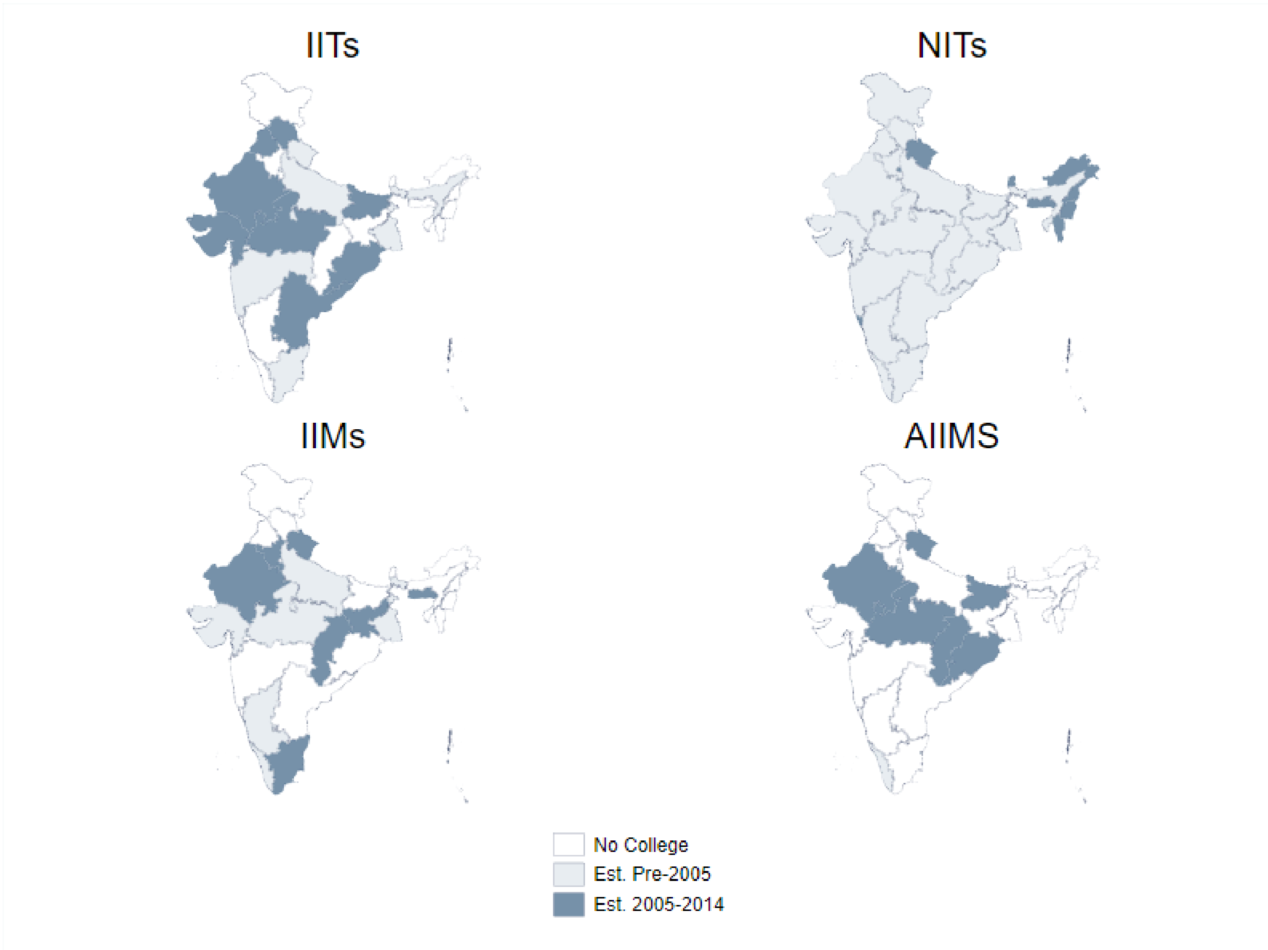
2200 hours at night. They use algorithms to filter out other sources of natural light using information about the lunar cycles, sunset times and the northern lights, and other occurrences like forest fires and cloud cover. The data is calculated at approximately every one square kilometer, but we aggregate up to the village level.

A.3.3 India Human Development Survey

In addition to the data sets mentioned in the main paper, we also make use of the India Human Development Survey (IHDS), which is a nationally representative, multi-topic survey conducted across urban and rural areas. There are currently two waves of IHDS (2004-05 and 2011-12), both of which we obtained from the survey's public portal. We use IHDS to examine the effects of elite public colleges on distance to private schools.

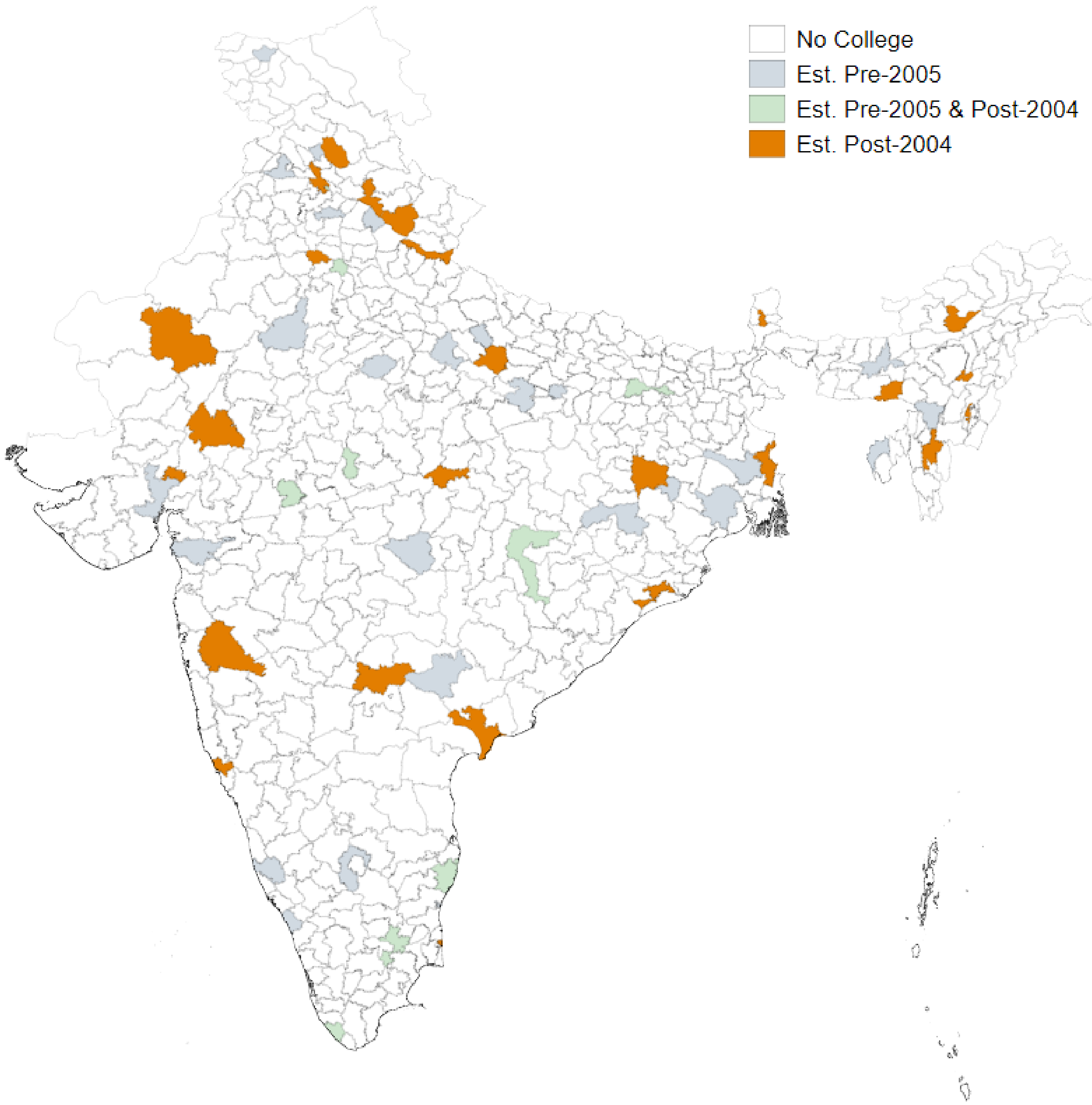
A.4 Figures

Figure A.1: States with Elite Public Colleges: Old vs. New



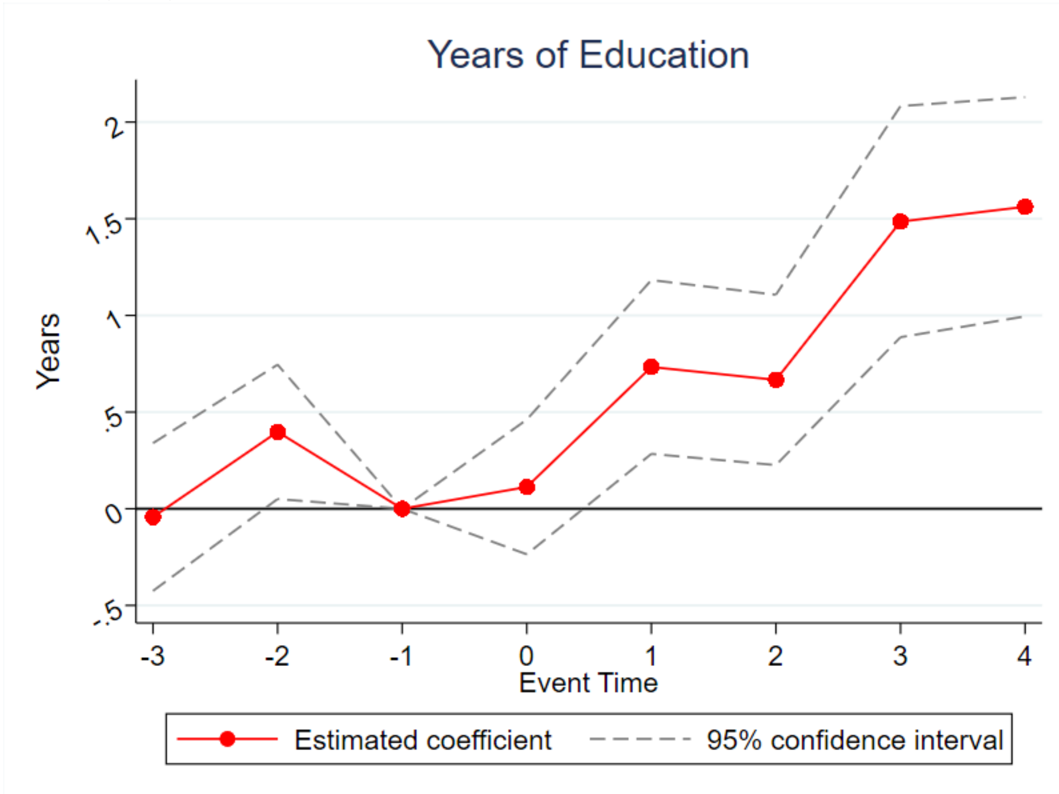
Notes: 'IITs': Indian Institute of Technology; 'NITs': National Institute of Technology; 'IIMs': Indian Institute of Mangement; 'AIIMS': All India Institute of Medical Sciences. These four types of elite public colleges constitute around 75 percent of all elite public colleges. This figure shows that states that had already received a type of elite public college before 2005 did not receive a new elite public college between 2005 and 2014. For instance, only states that did not have an elite public college an IIM before 2005, received an IIM between 2005 and 2014. Similar maps for elite colleges in other fields of study are available on request.

Figure A.2: Treatment (Elite Public College) Districts



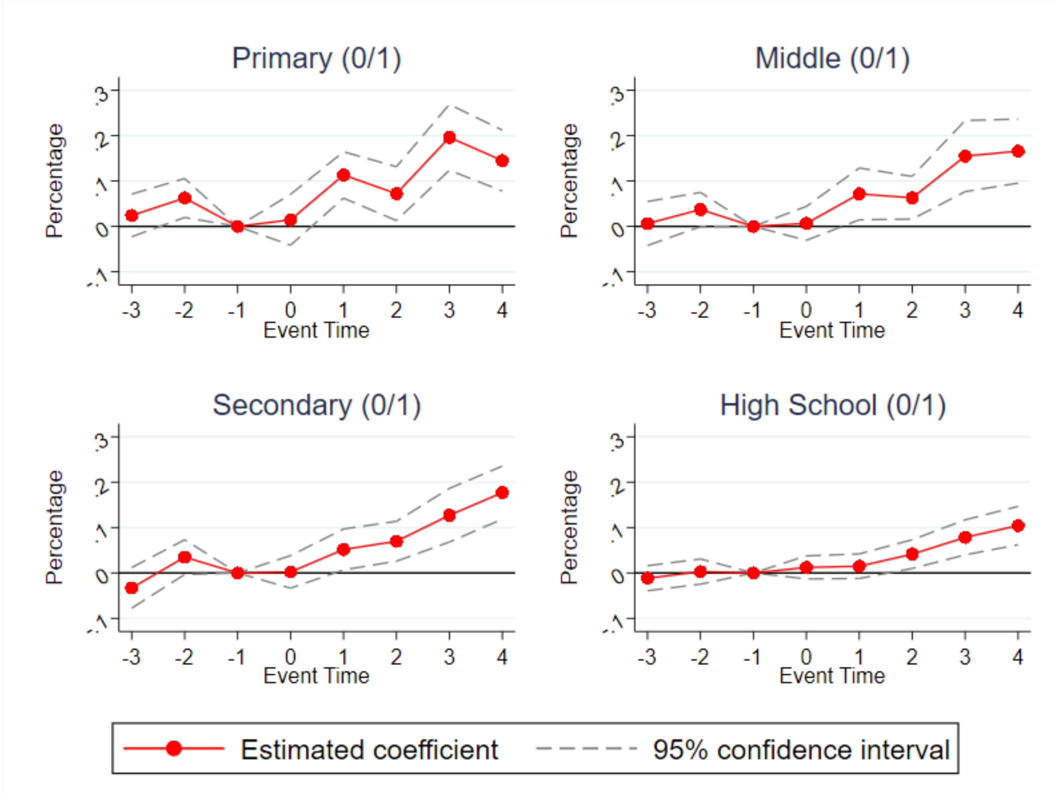
Notes: This figure shows the spatial distribution of old and new elite public colleges in India. 'Est. Pre-2005' indicates districts where elite public colleges were established before 2005. 'Est. Pre-2005 & Post-2004' indicates districts where elite public colleges were established both before 2005 and after 2004. 'Est. Post-2004' indicates our treatment districts or districts where elite public colleges were only established after 2004.

Figure A.3: Event Year Specification: Impact of Elite Public Colleges on Years of Schooling (Age 6-20)



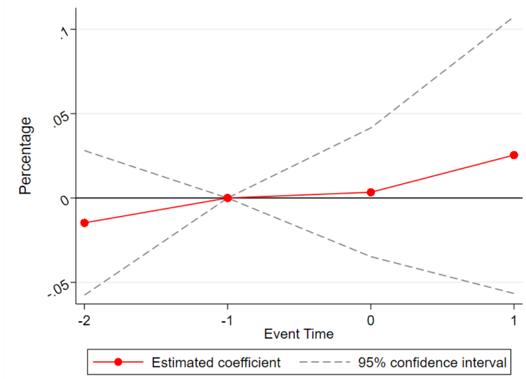
Notes: Sample includes a repeated cross-section of individuals between 6 and 20 years of age from a balanced district level panel of 25 treatment districts across 4 NSS survey rounds (2004, 2007, 2010 and 2012). The figure presents the effects of elite public colleges on years of schooling. $\tau = 0$ is the year of entry of elite public colleges. These estimates are average treatment effects of elite public colleges relative to the year before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2009, the NSS surveys conduced in 2004, 2007, 2010, and 2012 are denoted as $\tau = -5$, $\tau = -2$, $\tau = 1$ and $\tau = 3$, respectively. The regression, equation 2.3, includes district and round fixed effects. 95% confidence interval is presented, standard errors are clustered at the district level.

Figure A.4: Event Year Specification: Impact of Elite Public Colleges on Educational Attainment (Age 6-20)

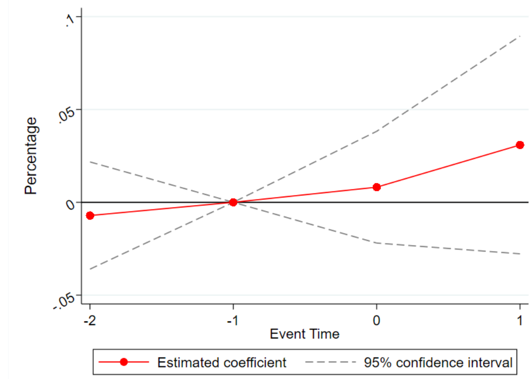


Notes: Sample includes a repeated cross-section of individuals between 6 and 20 years of age from a balanced district level panel of 25 treatment districts across 4 NSS survey rounds (2004, 2007, 2010 and 2012). The figure presents the effects of elite public colleges on educational attainment for four levels of schooling; primary school (0/1), middle school (0/1), secondary school (0/1), and high school (0/1). $\tau = 0$ is the year of entry of elite public colleges. These estimates are average treatment effects of elite public colleges on treated districts relative to the year before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2009, the NSS surveys conduced in 2004, 2007, 2010, and 2012 are denoted as $\tau = -5$, $\tau = -2$, $\tau = 1$ and $\tau = 3$, respectively. The regression, equation 2.3, includes district and round fixed effects. 95% confidence interval is presented, standard errors are clustered at the district level.

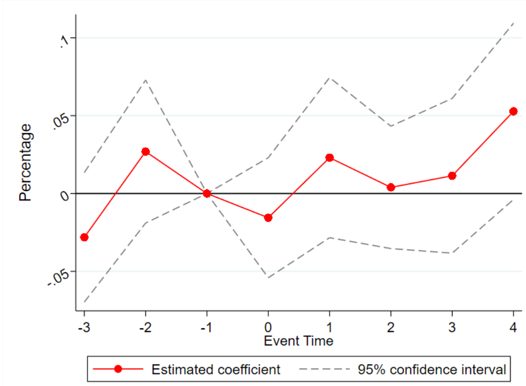
Figure A.5: Impact of Elite Public Colleges on Enrollment Status (0/1)



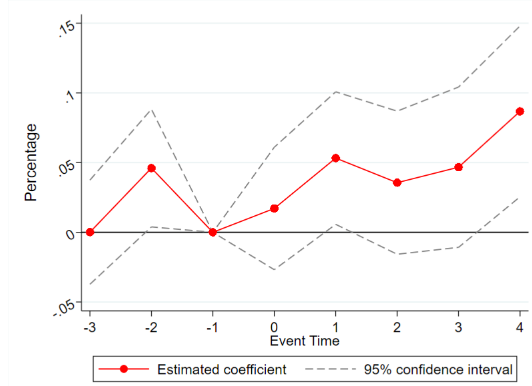
(a) Event-Survey-Round Specification: Age 6-20



(b) Event-Survey-Round Specification: Age 6-16



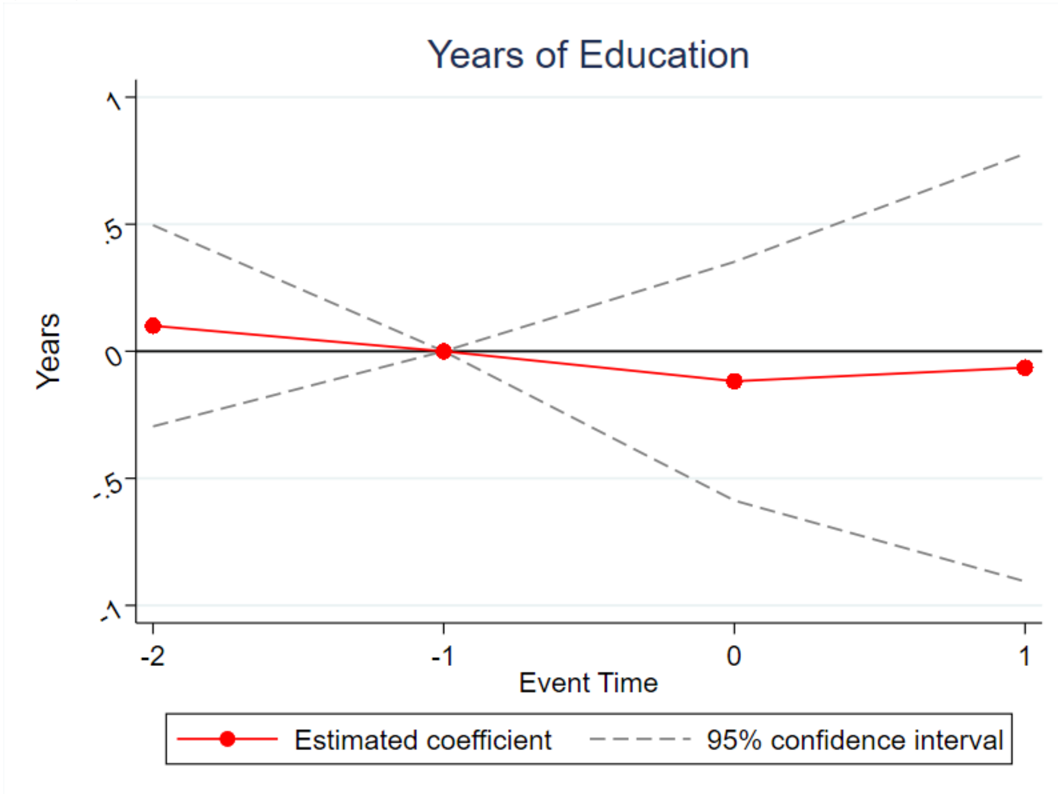
(c) Event-Year Specification: Age 6-20



(d) Event-Year Specification: Age 6-16

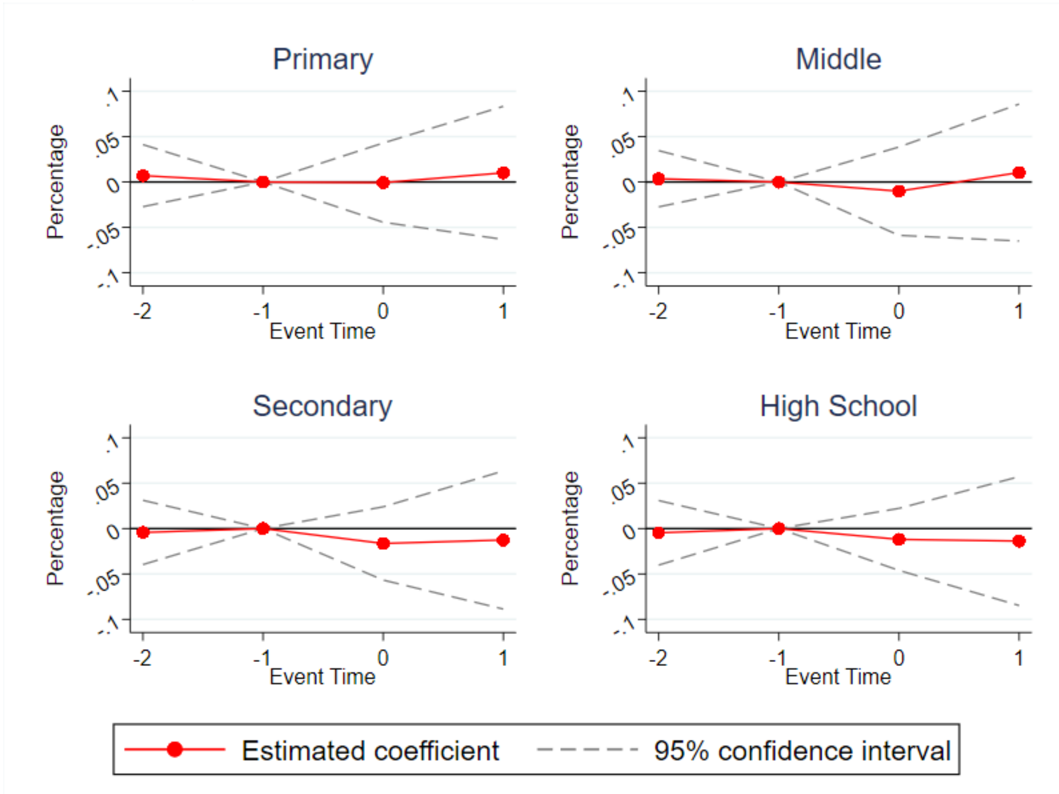
Notes: Sample includes a repeated cross-section of individuals between 6 and 20 years of age from a balanced district level panel of 25 treatment districts across 4 NSS survey rounds (2004, 2007, 2010 and 2012). The figure presents the effects of elite public colleges on enrollment status (0/1). In Panels (a) and (b), $\tau = 0$ is the *round* of entry of elite public colleges. These estimates are average treatment effects of elite public colleges on treated districts relative to the round before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2008, 2009 or 2010, the NSS surveys conduced in 2004, 2007, 2010, and 2012 are denoted as $\tau = -2$, $\tau = -1$, $\tau = 0$ and $\tau = 1$, respectively. In Panels (c) and (d), $\tau = 0$ is the *year* of entry of elite public colleges. These estimates are average treatment effects of elite public colleges on treated districts relative to the year before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2009, the NSS surveys conduced in 2004, 2007, 2010, and 2012 are denoted as $\tau = -5$, $\tau = -2$, $\tau = 1$ and $\tau = 3$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects. 95% confidence interval is presented, standard errors are clustered at the district level.

Figure A.6: Falsification Test: Impact of Elite Public Colleges on Years of Schooling (Age 21-65)



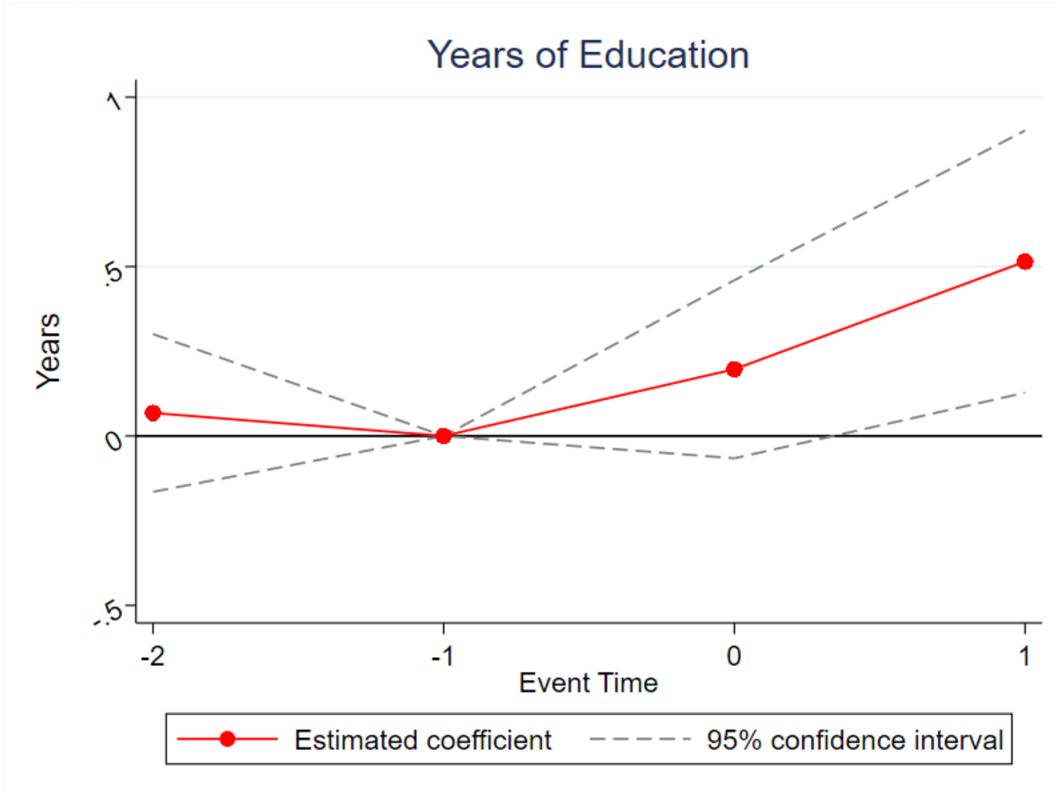
Notes: Sample includes a repeated cross-section of individuals between 21 and 65 years of age from a balanced district level panel of 25 treatment districts across 4 NSS survey rounds (2004, 2007, 2010 and 2012). The figure presents a falsification test, that is, the effects of elite public colleges on years of schooling for individuals above the school-going age. $\tau = 0$ is the round of entry of elite public colleges. These are average treatment effects on treated districts of elite public colleges relative to the round before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2008, 2009 or 2010, the NSS surveys conduced in 2004, 2007, 2010, and 2012 are denoted as $\tau = -2$, $\tau = -1$, $\tau = 0$ and $\tau = 1$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects. 95% confidence interval is presented, standard errors are clustered at the district level.

Figure A.7: Falsification Test: Impact of Elite Public Colleges on Educational Attainment (Age 21-65)



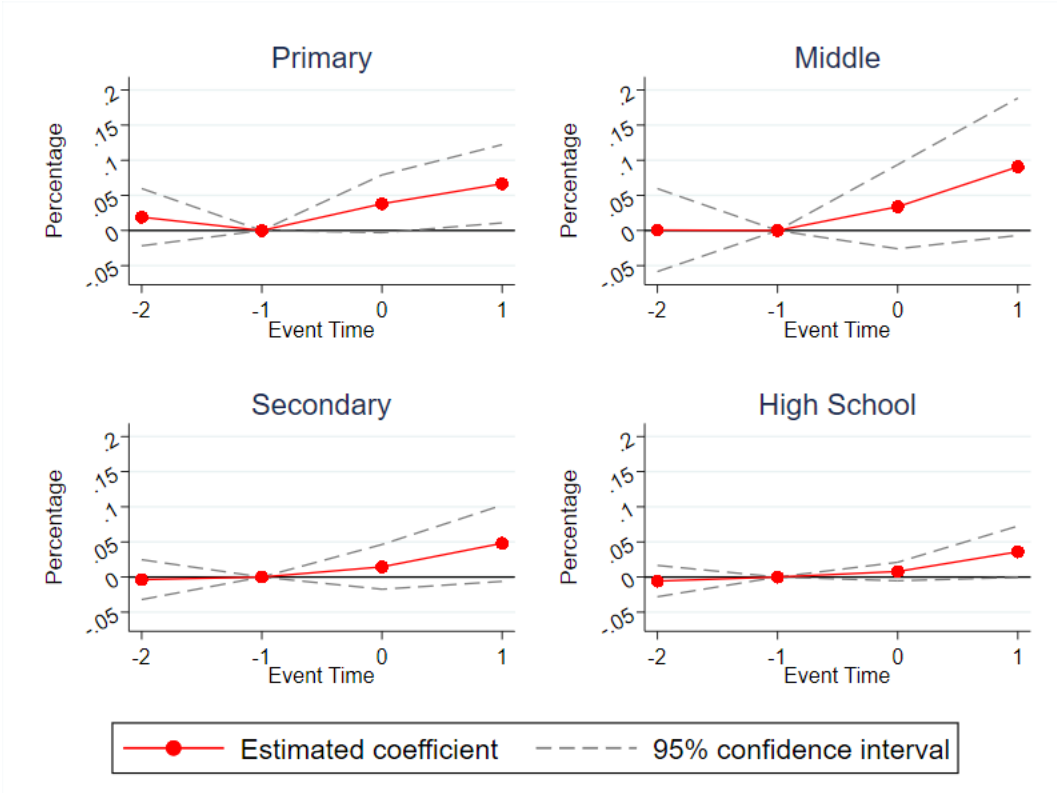
Notes: Sample includes a repeated cross-section of individuals between 21 and 65 years of age from a balanced district level panel of 25 treatment districts across 4 NSS survey rounds (2004, 2007, 2010 and 2012). The figure presents a falsification test, that is, the effects of elite public colleges on educational attainment for individuals above the school-going age. The figure presents the effects of elite public colleges on educational attainment for four levels of schooling; primary school (0/1), middle school (0/1), secondary school (0/1), and high school (0/1). $\tau = 0$ is the round of entry of elite public colleges. These are average treatment effects on treated districts of elite public colleges relative to the round before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2008, 2009 or 2010, the NSS surveys conduced in 2004, 2007, 2010, and 2012 are denoted as $\tau = -2$, $\tau = -1$, $\tau = 0$ and $\tau = 1$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects. 95% confidence intervals are presented, standard errors are clustered at the district level.

Figure A.8: Control for Age: Impact of Elite Public Colleges on Years of Schooling (Age 6-20)



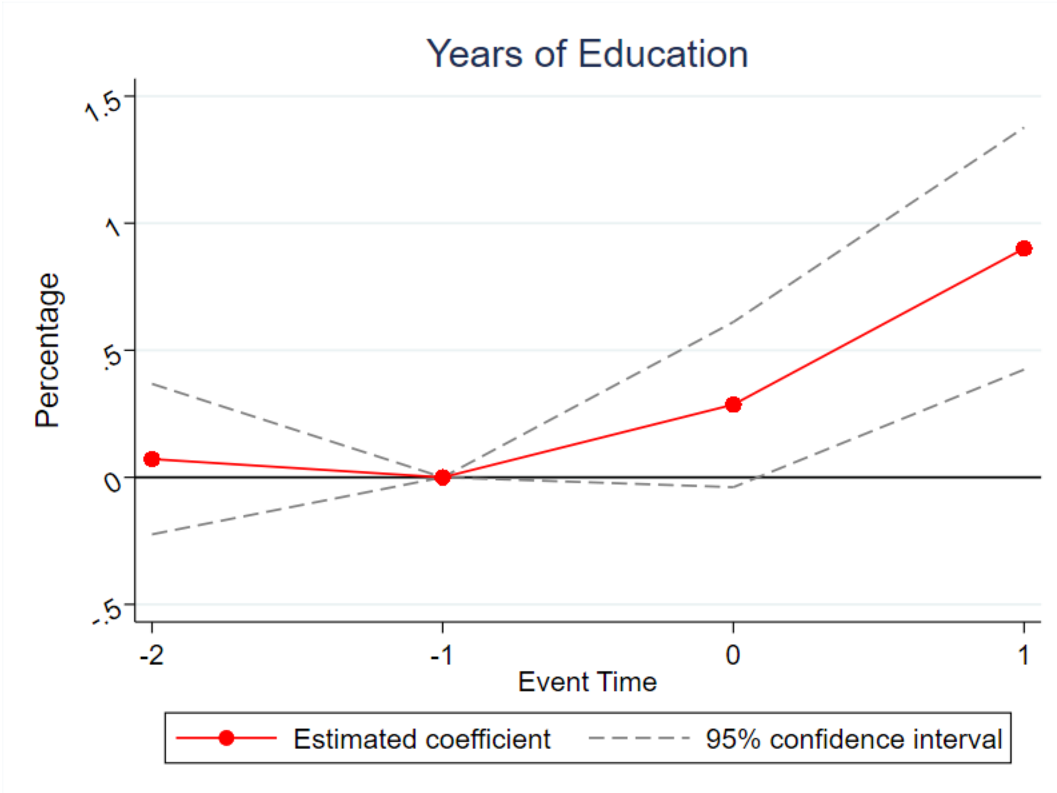
Notes: Sample includes a repeated cross-section of individuals between 6 and 20 years of age from a balanced district level panel of 25 treatment districts across 4 NSS survey rounds (2004, 2007, 2010 and 2012). The figure presents the effects of elite public colleges on years of schooling. $\tau = 0$ is the round of entry of elite public colleges. These are average treatment effects on treated districts of elite public colleges relative to the round before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2008, 2009 or 2010, the NSS surveys conduced in 2004, 2007, 2010, and 2012 are denoted as $\tau = -2$, $\tau = -1$, $\tau = 0$ and $\tau = 1$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects as well as controls for age. 95% confidence interval is presented, standard errors are clustered at the district level.

Figure A.9: Control for Age: Impact of Elite Public Colleges on Educational Attainment (Age 6-20)



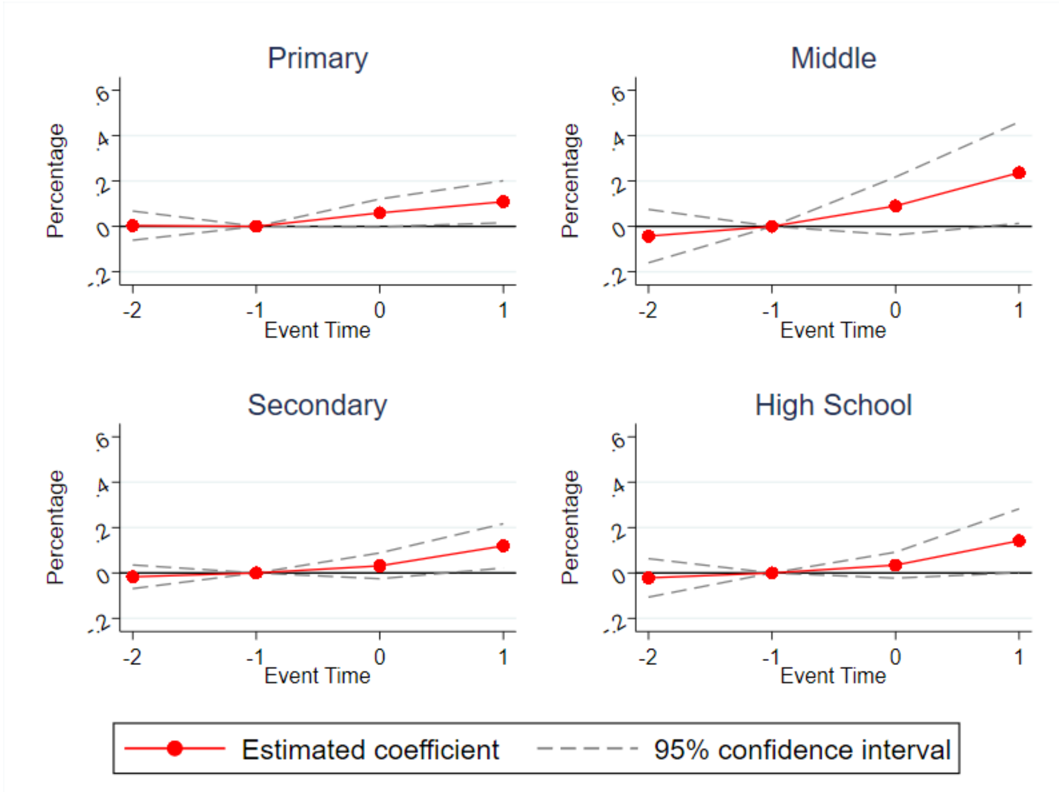
Notes: Sample includes a repeated cross-section of individuals between 6 and 20 years of age from a balanced district level panel of 25 treatment districts across 4 NSS survey rounds (2004, 2007, 2010 and 2012). The figure presents the effects of elite public colleges on educational attainment for four levels of schooling; primary school (0/1), middle school (0/1), secondary school (0/1), and high school (0/1). $\tau = 0$ is the round of entry of elite public colleges. These are average treatment effects on treated districts of elite public colleges relative to the round before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2008, 2009 or 2010, the NSS surveys conduced in 2004, 2007, 2010, and 2012 are denoted as $\tau = -2$, $\tau = -1$, $\tau = 0$ and $\tau = 1$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects as well as controls for age. 95% confidence intervals are presented, standard errors are clustered at the district level.

Figure A.10: Older Children: Impact of Elite Public Colleges on Years of Schooling (Age 9-16)



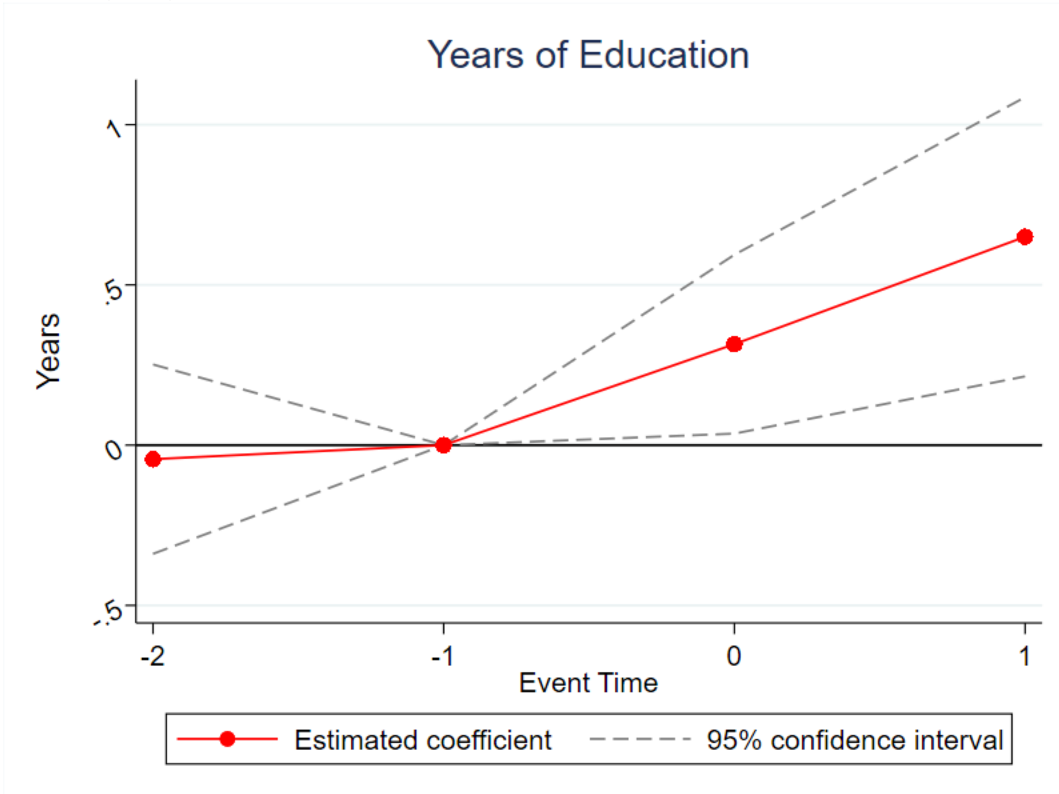
Notes: Sample includes a repeated cross-section of individuals between 9 and 16 years of age from a balanced district level panel of 25 treatment districts across 4 NSS survey rounds (2004, 2007, 2010 and 2012). The figure presents the effects of elite public colleges on years of schooling. $\tau = 0$ is the round of entry of elite public colleges. These are average treatment effects on treated districts of elite public colleges relative to the round before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2008, 2009 or 2010, the NSS surveys conduced in 2004, 2007, 2010, and 2012 are denoted as $\tau = -2$, $\tau = -1$, $\tau = 0$ and $\tau = 1$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects as well as controls for age. 95% confidence interval is presented, standard errors are clustered at the district level.

Figure A.11: Age-Appropriate Sample: Impact of Elite Public Colleges on Educational Attainment



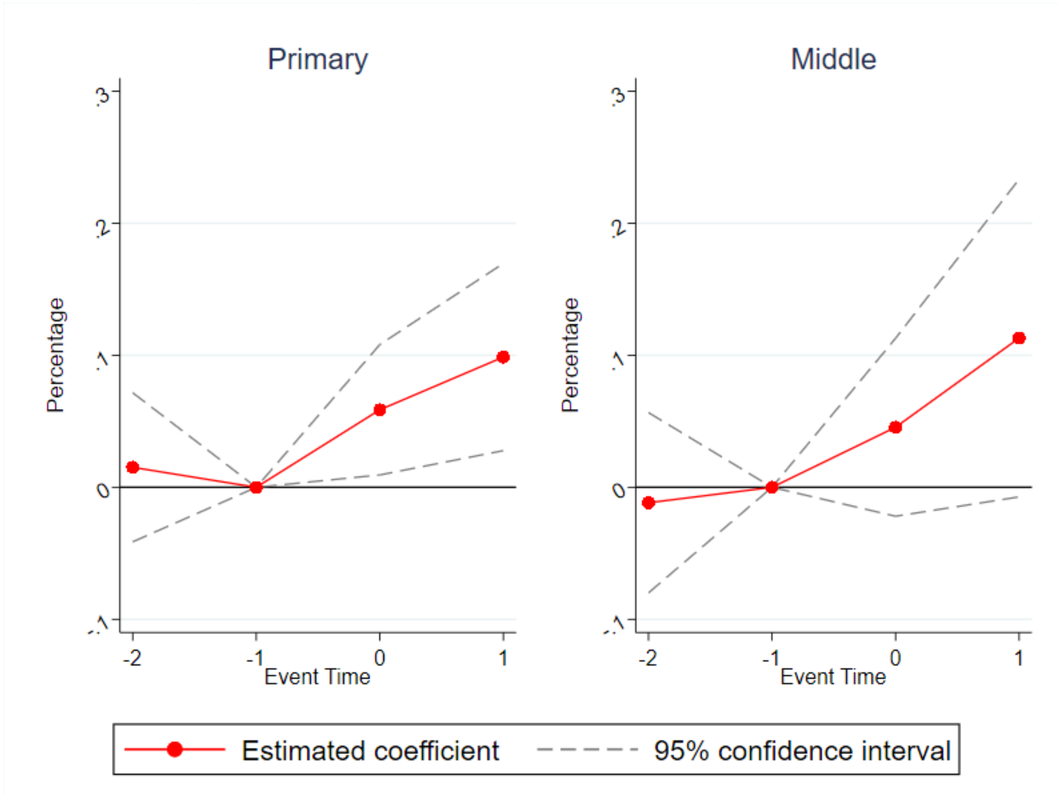
Notes: Sample includes a repeated cross-section of individuals between 6 and 20 years of age from a balanced district level panel of 25 treatment districts across 4 NSS survey rounds (2004, 2007, 2010 and 2012). The figure presents the effects of elite public colleges on educational attainment for four levels of schooling; primary school (0/1), middle school (0/1), secondary school (0/1), and high school (0/1). The sample is restricted to children between 9 and 16 years of age for primary school, between 12 and 16 years of age for middle school, between 14 and 20 years of age for secondary school, and between 17 and 20 years of age for high school. $\tau = 0$ is the round of entry of elite public colleges. These are average treatment effects on treated districts of elite public colleges relative to the round before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2008, 2009 or 2010, the NSS surveys conduced in 2004, 2007, 2010, and 2012 are denoted as $\tau = -2$, $\tau = -1$, $\tau = 0$ and $\tau = 1$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects. 95% confidence intervals are presented, standard errors are clustered at the district level.

Figure A.12: Younger Children: Impact of Elite Public Colleges on Years of Schooling (Age 6-16)



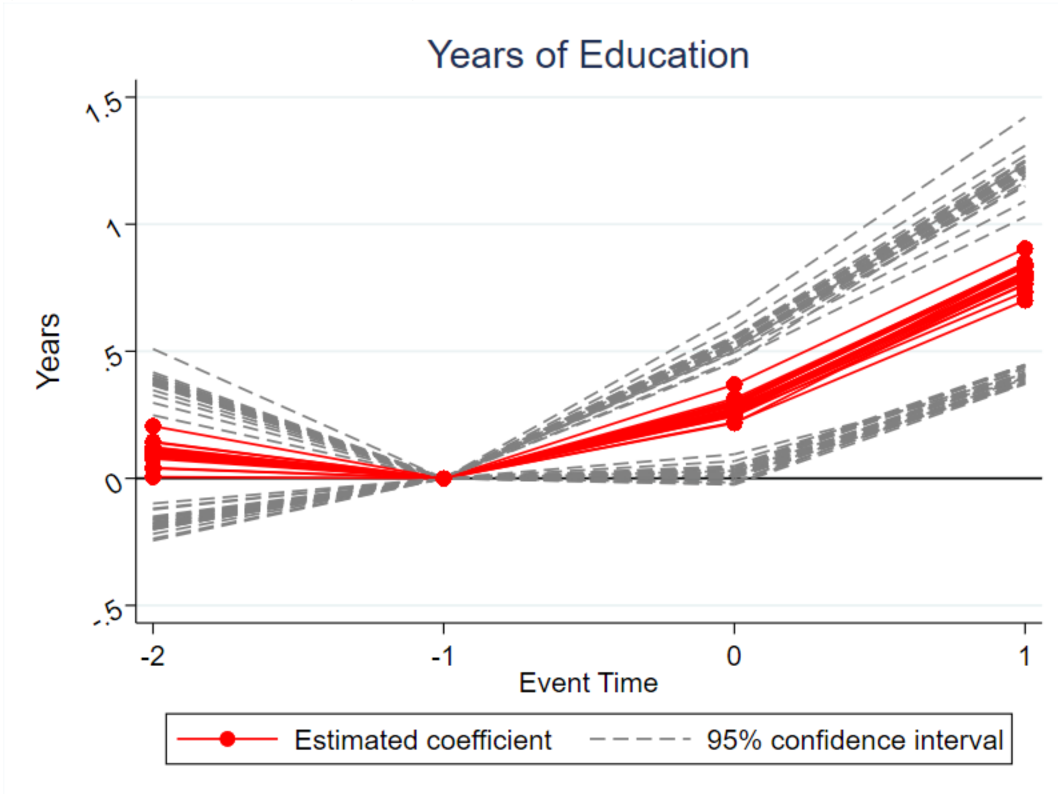
Notes: Sample includes a repeated cross-section of individuals between 6 and 16 years of age from a balanced district level panel of 25 treatment districts across 4 NSS survey rounds (2004, 2007, 2010 and 2012). The figure presents the effects of elite public colleges on years of schooling. $\tau = 0$ is the round of entry of elite public colleges. These are average treatment effects on treated districts of elite public colleges relative to the round before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2008, 2009 or 2010, the NSS surveys conduced in 2004, 2007, 2010, and 2012 are denoted as $\tau = -2$, $\tau = -1$, $\tau = 0$ and $\tau = 1$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects as well as controls for age. 95% confidence interval is presented, standard errors are clustered at the district level.

Figure A.13: Younger Children: Impact of Elite Public Colleges on Educational Attainment (Age 6-16)



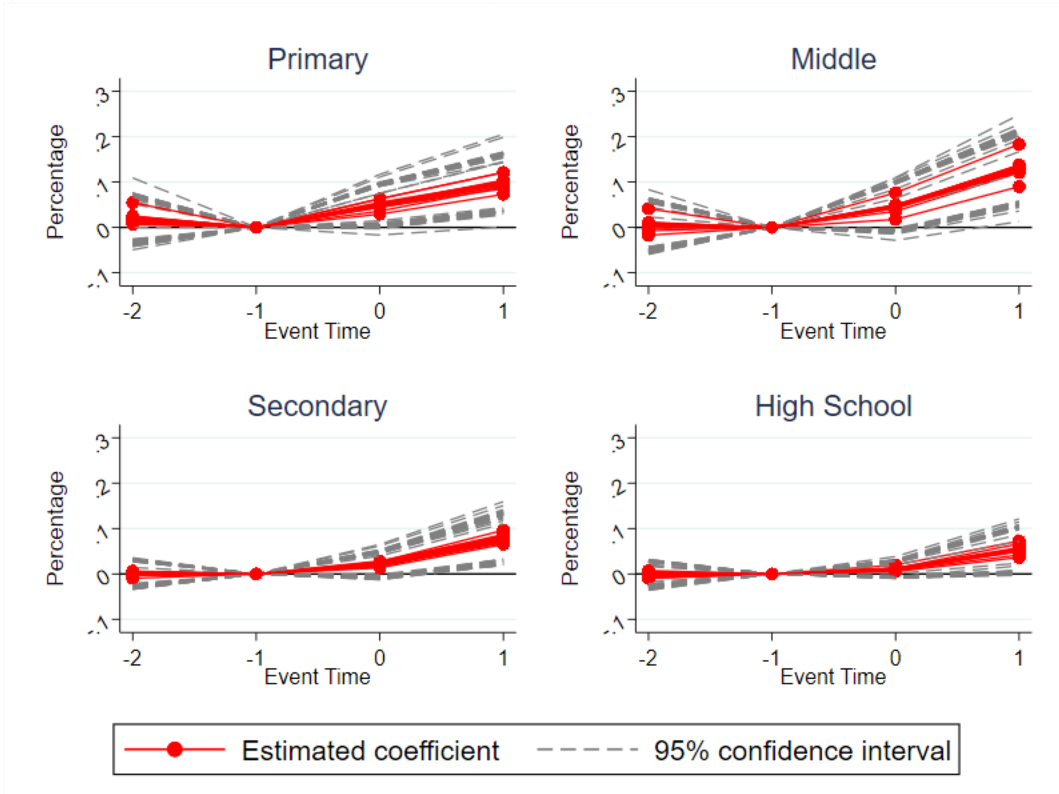
Notes: Sample includes a repeated cross-section of individuals between 6 and 16 years of age from a balanced district level panel of 25 treatment districts across 4 NSS survey rounds (2004, 2007, 2010 and 2012). The figure presents the effects of elite public colleges on educational attainment for four levels of schooling; primary school (0/1) and middle school (0/1). $\tau = 0$ is the round of entry of elite public colleges. These are average treatment effects on treated districts of elite public colleges relative to the round before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2008, 2009 or 2010, the NSS surveys conduced in 2004, 2007, 2010, and 2012 are denoted as $\tau = -2$, $\tau = -1$, $\tau = 0$ and $\tau = 1$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects as well as controls for age. 95% confidence intervals are presented, standard errors are clustered at the district level.

Figure A.14: Dropping Each District, One-by-One: Impact of Elite Public Colleges on Years of Schooling (Age 6-20)



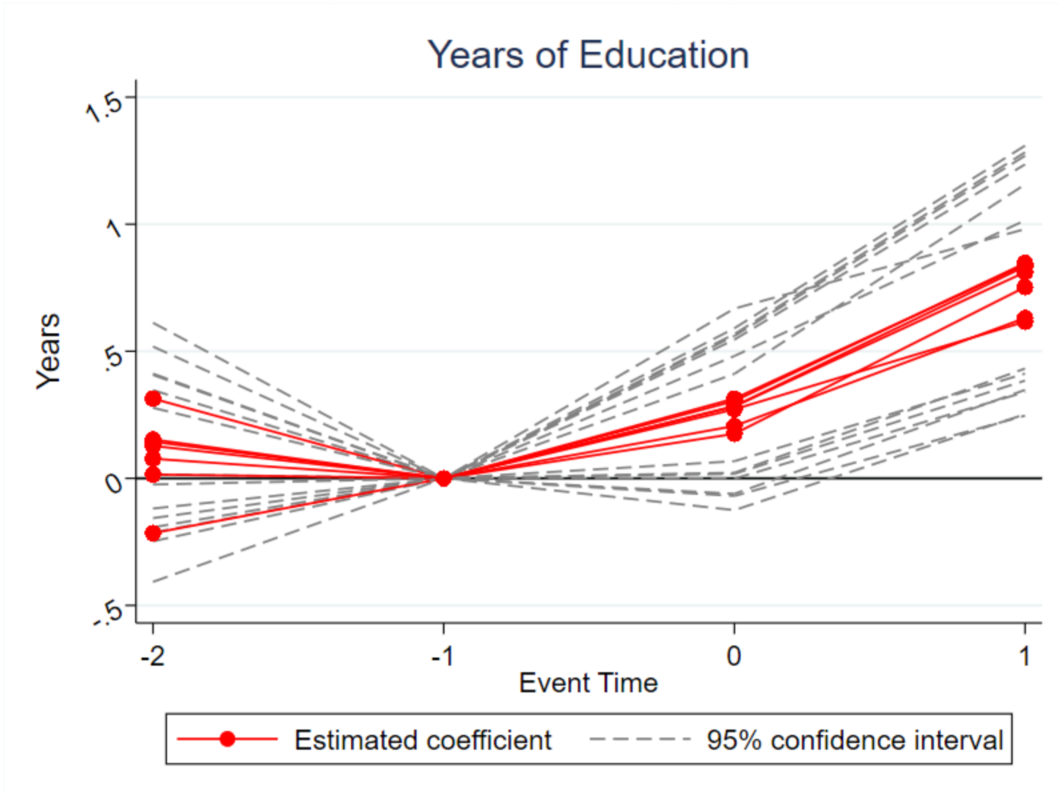
Notes: Sample includes a repeated cross-section of individuals between 6 and 20 years of age from a balanced district level panel of 25 treatment districts across 4 NSS survey rounds (2004, 2007, 2010 and 2012). The figure presents the effects of elite public colleges on years of schooling. The figure presents results from 25 regressions, each time dropping one treatment district. $\tau = 0$ is the round of entry of elite public colleges. These are average treatment effects on treated districts of elite public colleges relative to the round before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2008, 2009 or 2010, the NSS surveys conduced in 2004, 2007, 2010, and 2012 are denoted as $\tau = -2$, $\tau = -1$, $\tau = 0$ and $\tau = 1$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects. 95% confidence interval is presented, standard errors are clustered at the district level.

Figure A.15: Dropping Each District, One-by-One: Impact of Elite Public Colleges on Educational Attainment (Age 6-20)



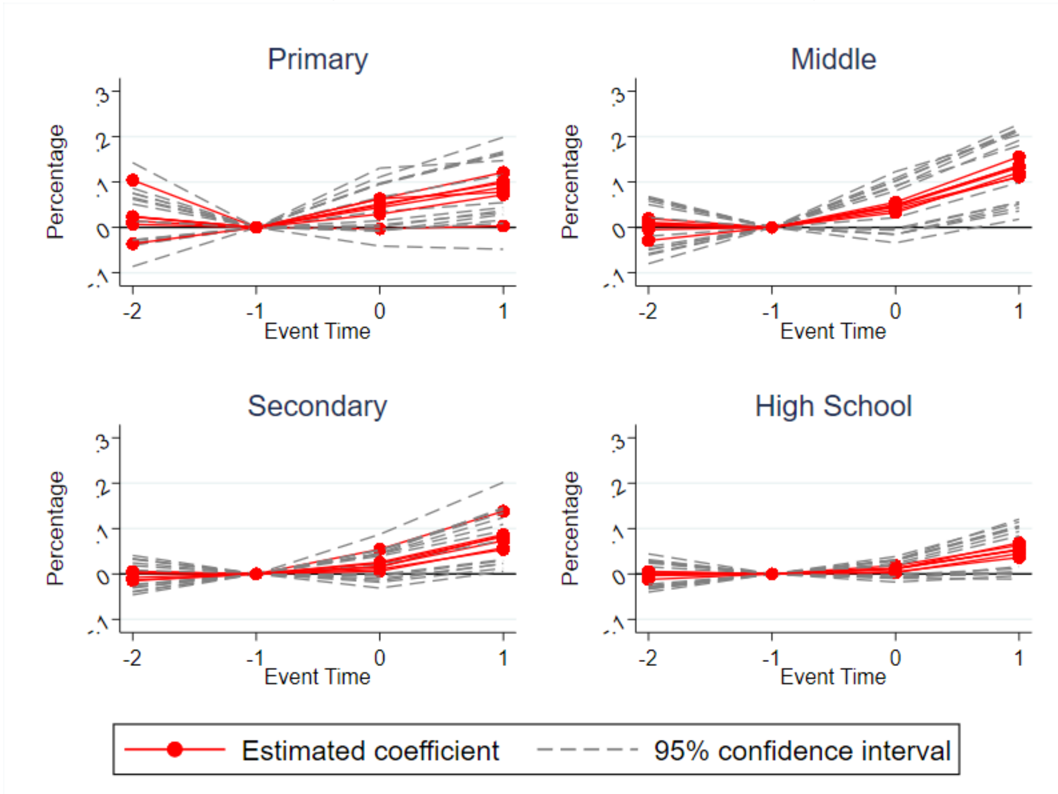
Notes: Sample includes a repeated cross-section of individuals between 6 and 20 years of age from a balanced district level panel of 25 treatment districts across 4 NSS survey rounds (2004, 2007, 2010 and 2012). The figure presents the effects of elite public colleges on educational attainment for four levels of schooling; primary school (0/1), middle school (0/1), secondary school (0/1), and high school (0/1). Each panel in the figure presents results from 25 regressions, each time dropping one treatment district. $\tau = 0$ is the round of entry of elite public colleges. These are average treatment effects on treated districts of elite public colleges relative to the round before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2008, 2009 or 2010, the NSS surveys conduced in 2004, 2007, 2010, and 2012 are denoted as $\tau = -2$, $\tau = -1$, $\tau = 0$ and $\tau = 1$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects. 95% confidence intervals are presented, standard errors are clustered at the district level.

Figure A.16: Dropping all Year-Specific Treatment Districts, One-by-One: Impact of Elite Public Colleges on Years of Schooling (Age 6-20)



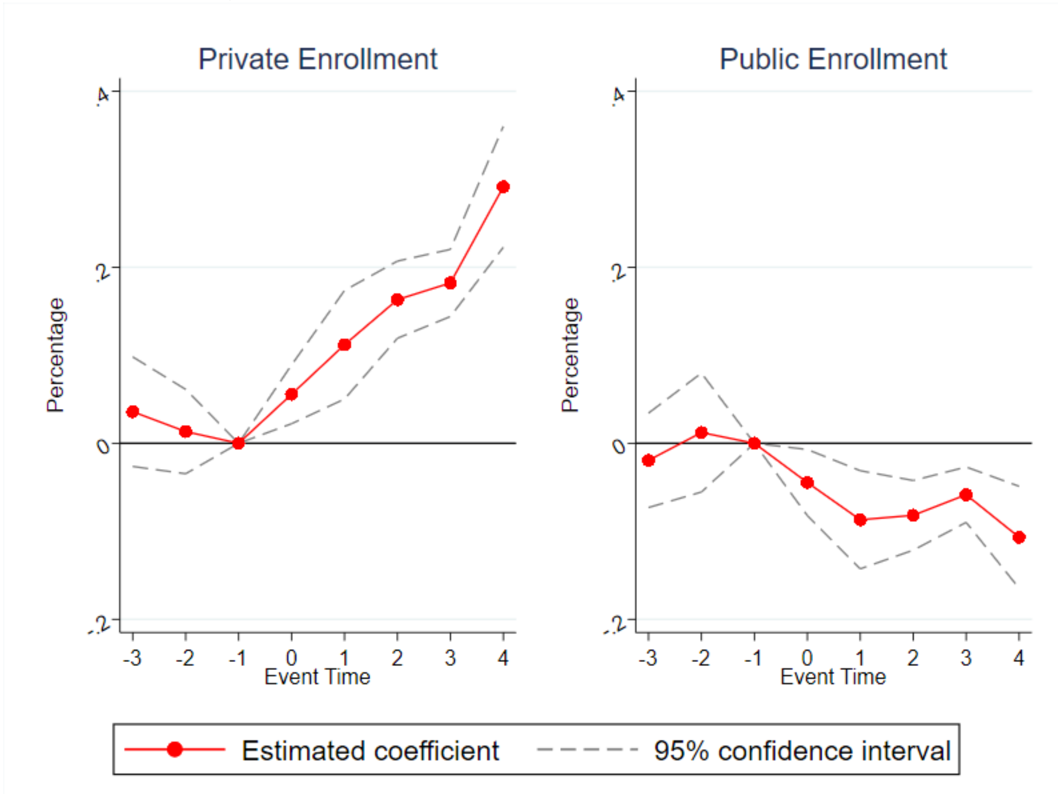
Notes: Sample includes a repeated cross-section of individuals between 6 and 20 years of age from a balanced district level panel of 25 treatment districts across 4 NSS survey rounds (2004, 2007, 2010 and 2012). The figure presents the effects of elite public colleges on years of schooling. The figure presents results from 7 regressions, each time dropping all treatment districts that received an elite public college in a specific year. $\tau = 0$ is the round of entry of elite public colleges. These are average treatment effects on treated districts of elite public colleges relative to the round before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2008, 2009 or 2010, the NSS surveys conduced in 2004, 2007, 2010, and 2012 are denoted as $\tau = -2$, $\tau = -1$, $\tau = 0$ and $\tau = 1$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects. 95% confidence interval is presented, standard errors are clustered at the district level.

Figure A.17: Dropping all Year-Specific Treatment Districts, One-by-One: Impact of Elite Public Colleges on Educational Attainment (Age 6-20)



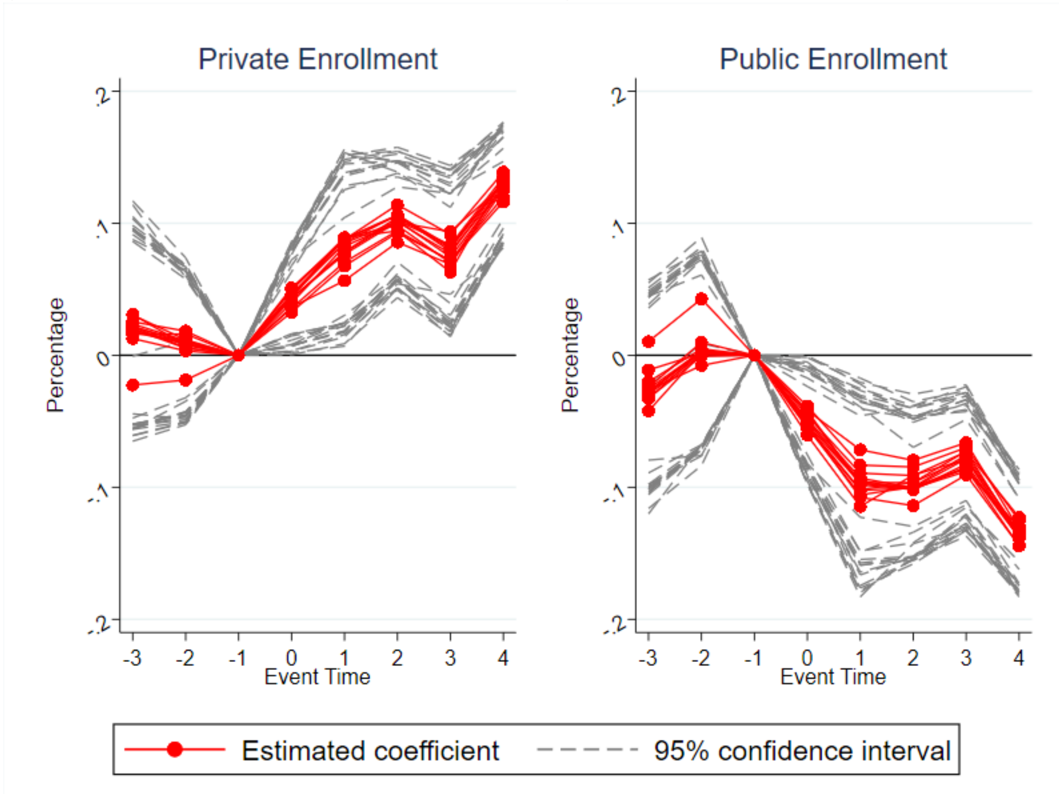
Notes: Sample includes a repeated cross-section of individuals between 6 and 20 years of age from a balanced district level panel of 25 treatment districts across 4 NSS survey rounds (2004, 2007, 2010 and 2012). The figure presents the effects of elite public colleges on educational attainment for four levels of schooling; primary school (0/1), middle school (0/1), secondary school (0/1), and high school (0/1). Each panel in the figure presents results from 7 regressions, each time dropping all treatment districts that received an elite public college in a specific year. $\tau = 0$ is the round of entry of elite public colleges. These are average treatment effects on treated districts of elite public colleges relative to the round before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2008, 2009 or 2010, the NSS surveys conduced in 2004, 2007, 2010, and 2012 are denoted as $\tau = -2$, $\tau = -1$, $\tau = 0$ and $\tau = 1$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects. 95% confidence intervals are presented, standard errors are clustered at the district level.

Figure A.18: Other Controls: Impact of Elite Public Colleges on Private vs. Public Enrollment (Age 5-16)



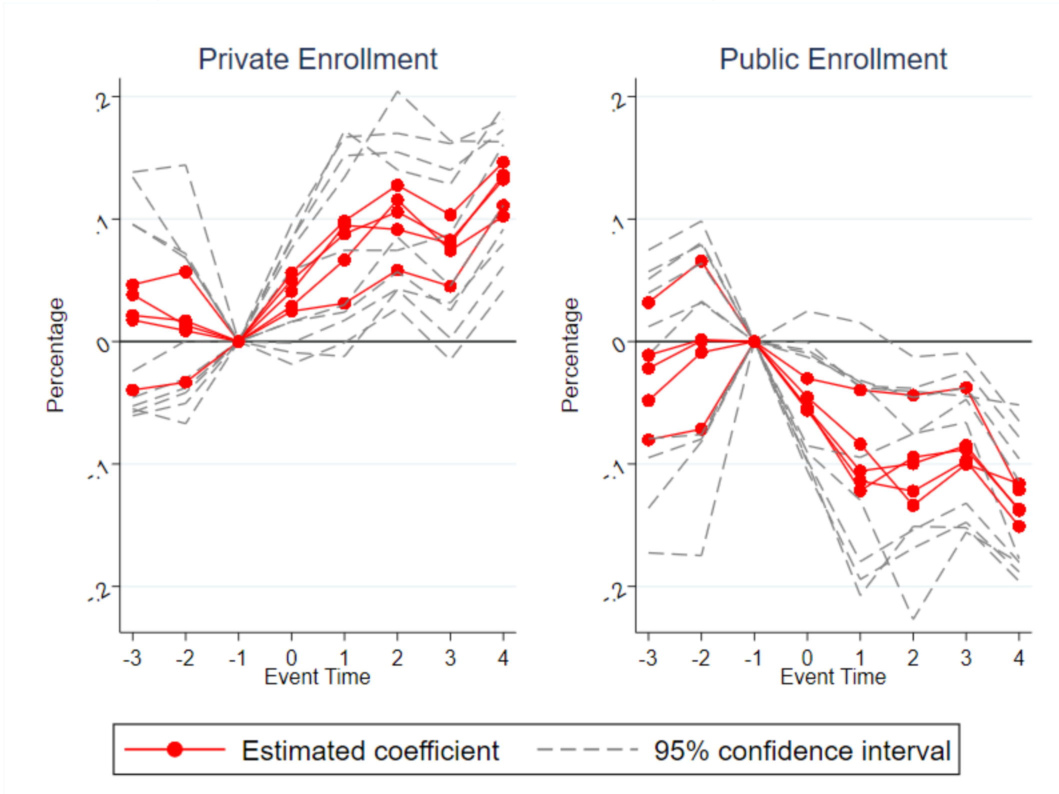
Notes: Sample includes a repeated cross-section of individuals between 5 and 16 years of age from a balanced district level panel of 14 treatment districts across 9 years of ASER data (2006-2014). The figure presents the effects of elite public colleges on private school (0/1) vs. public school (0/1) enrollment status. $\tau = 0$ is the year of entry of elite public colleges. These estimates are average treatment effects of elite public colleges relative to the year before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2009, the ASER surveys conduced in 2006, 2007, 2008, 2009, 2010, 2011, 2012, and 2013 are denoted as $\tau = -3$, $\tau = -2$, $\tau = -1$, $\tau = 0$, $\tau = 1$, $\tau = 2$, $\tau = 3$ and $\tau = 4$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects as well as controls for district-specific linear trends, age, and gender. 95% confidence intervals are presented, standard errors are clustered at the district level.

Figure A.19: Dropping Each District, One-by-One: Impact of Elite Public Colleges on Private vs. Public Enrollment (Age 5-16)



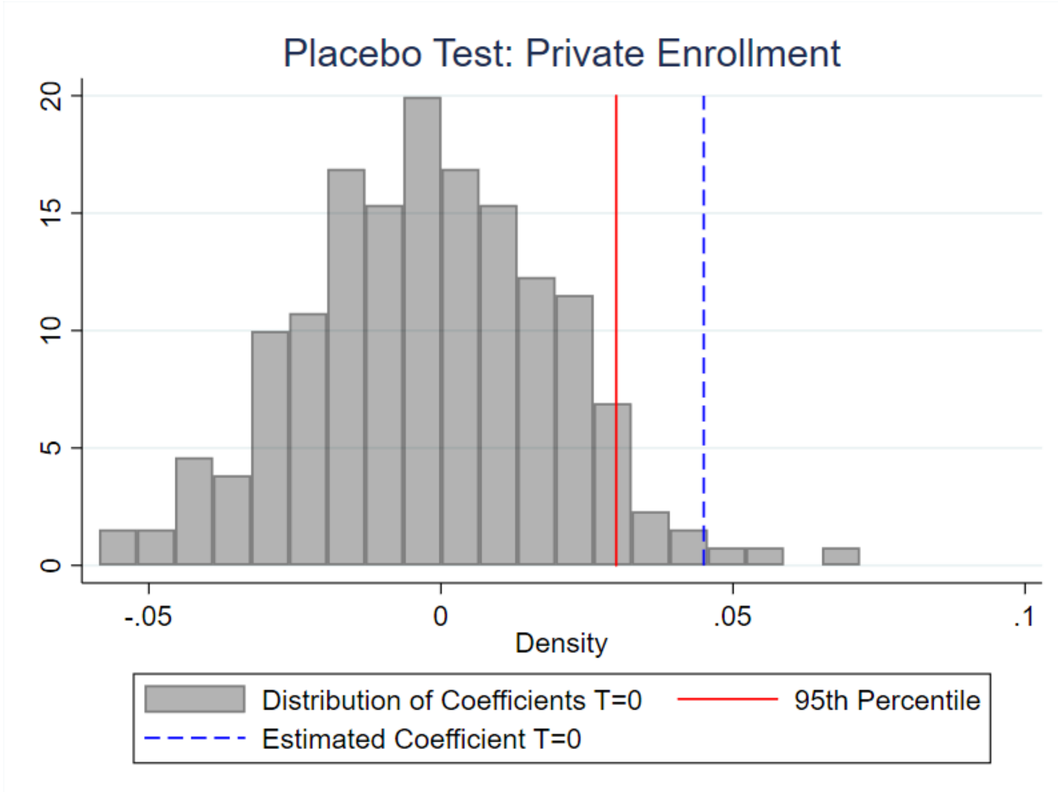
Notes: Sample includes a repeated cross-section of individuals between 5 and 16 years of age from a balanced district level panel of 14 treatment districts across 9 years of ASER data (2006-2014). The figure presents the effects of elite public colleges on private school (0/1) vs. public school (0/1) enrollment status. The figure presents results from 14 regressions, each time dropping one treatment district. $\tau = 0$ is the year of entry of elite public colleges. These estimates are average treatment effects of elite public colleges relative to the year before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2009, the ASER surveys conduced in 2006, 2007, 2008, 2009, 2010, 2011, 2012, and 2013 are denoted as $\tau = -3$, $\tau = -2$, $\tau = -1$, $\tau = 0$, $\tau = 1$, $\tau = 2$, $\tau = 3$ and $\tau = 4$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects. 95% confidence intervals are presented, standard errors are clustered at the district level.

Figure A.20: Dropping all Year-Specific Districts, One-by-One: Impact of Elite Public Colleges on Private vs. Public Enrollment (Age 5-16)



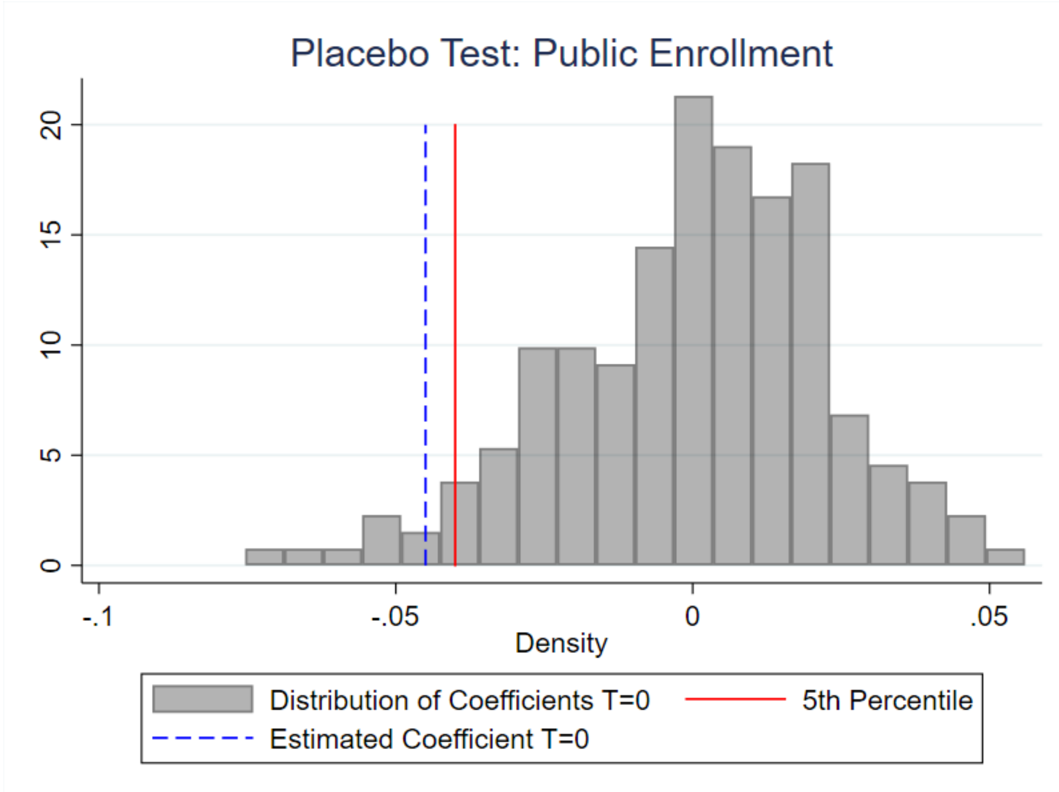
Notes: Sample includes a repeated cross-section of individuals between 5 and 16 years of age from a balanced district level panel of 14 treatment districts across 9 years of ASER data (2006-2014). The figure presents the effects of elite public colleges on private school (0/1) vs. public school (0/1) enrollment status. The figure presents results from 7 regressions, each time dropping all treatment districts that received an elite public college in a specific year. These estimates are average treatment effects of elite public colleges relative to the year before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2009, the ASER surveys conduced in 2006, 2007, 2008, 2009, 2010, 2011, 2012, and 2013 are denoted as $\tau = -3$, $\tau = -2$, $\tau = -1$, $\tau = 0$, $\tau = 1$, $\tau = 2$, $\tau = 3$ and $\tau = 4$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects. 95% confidence intervals are presented, standard errors are clustered at the district level.

Figure A.21: Placebo Test: Impact of Elite Public Colleges on Private Enrollment at $T = 0$



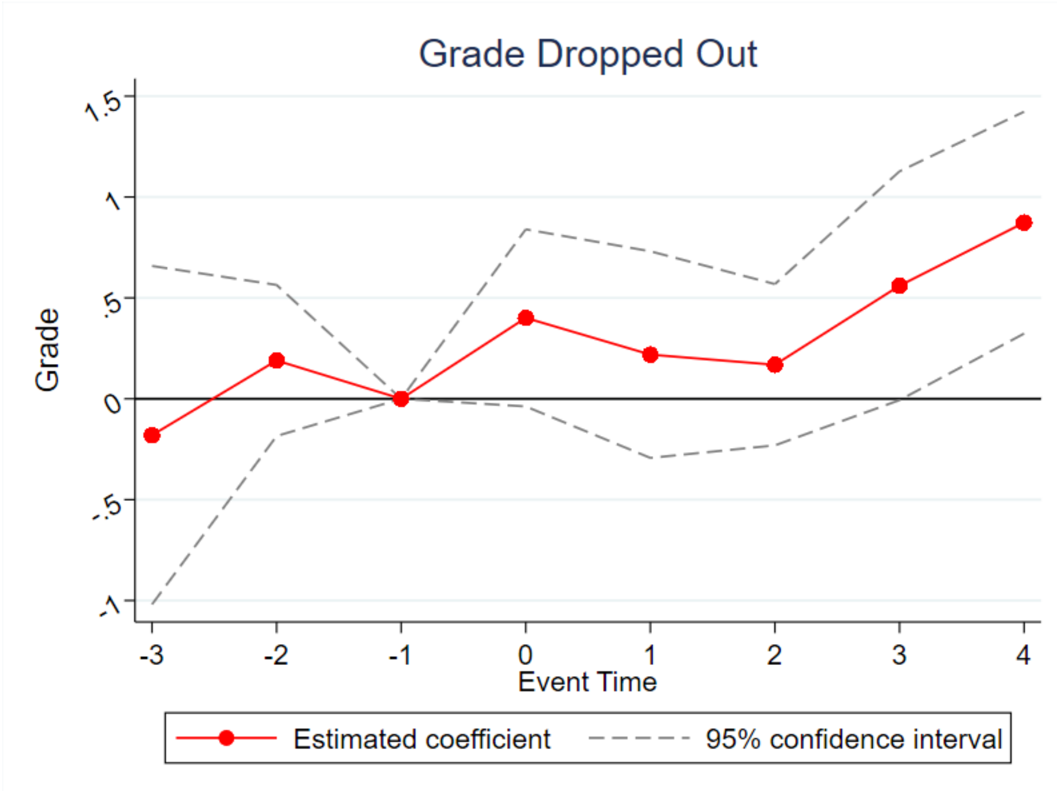
Notes: Sample includes a repeated cross-section of individuals between 5 and 16 years of age from a balanced district level panel of 14 treatment districts across 9 years of ASER data (2006-2014). The figure presents the distribution of the (placebo) estimates of the effects of elite public colleges on private enrollment status (0/1) at $\tau = 0$ or year of entry of elite public colleges, when the year of entry is randomly assigned amongst treated districts. That is, it presents the distribution of estimates at $\tau = 0$ from 200 regressions, randomly assigning the year of entry of elite public colleges among treatment districts each time. Regressions includes district and year (round) fixed effects. The blue dashed line denotes the observed effect size at $\tau = 0$ from the baseline regression, and the solid red line indicates the 95% percentile of the distribution of the placebo estimates.

Figure A.22: Placebo Test: Impact of Elite Public Colleges on Public Enrollment at $T = 0$



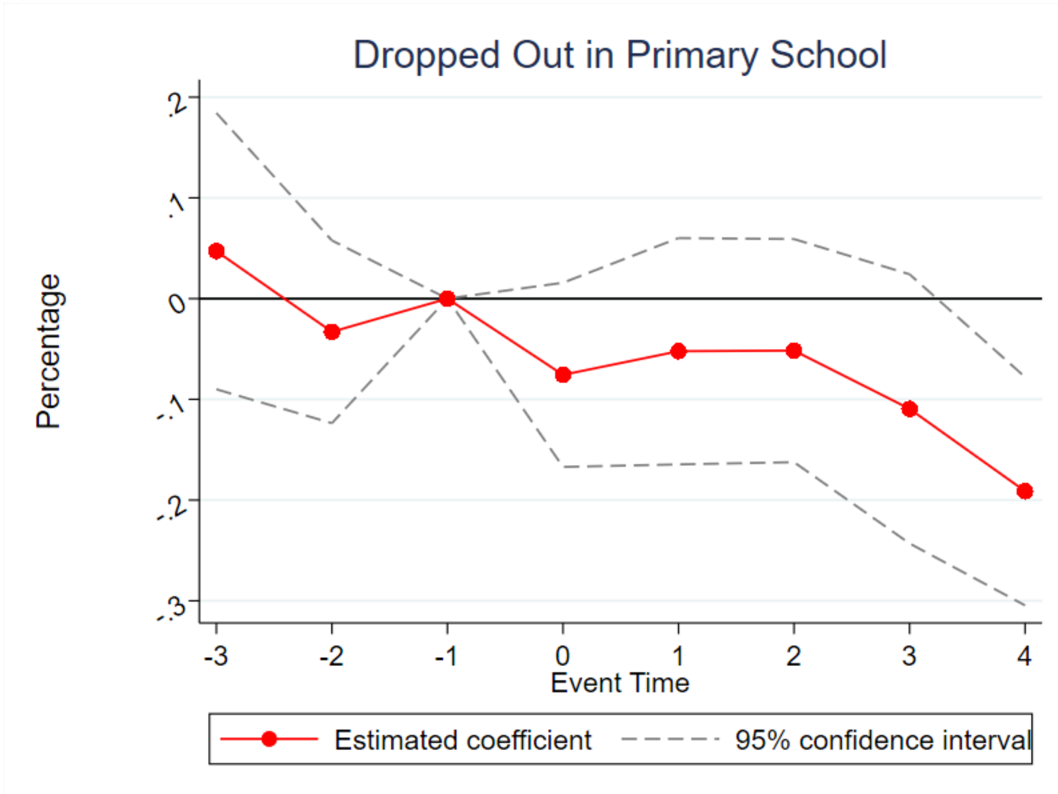
Notes: Sample includes a repeated cross-section of individuals between 5 and 16 years of age from a balanced district level panel of 14 treatment districts across 9 years of ASER data (2006-2014). The figure presents the distribution of the (placebo) estimates of the effects of elite public colleges on public enrollment status (0/1) at $\tau = 0$ or year of entry of elite public colleges, when the year of entry is randomly assigned amongst treated districts. That is, it presents the distribution of estimates at $\tau = 0$ from 200 regressions, randomly assigning the year of entry of elite public colleges among treatment districts each time. Regressions includes district and year (round) fixed effects. The blue dashed line denotes the observed effect size at $\tau = 0$ from the baseline regression, and the solid red line indicates the 95% percentile of the distribution of the placebo estimates.

Figure A.23: Impact of Elite Public Colleges on Dropout Grade (Age 5-16)



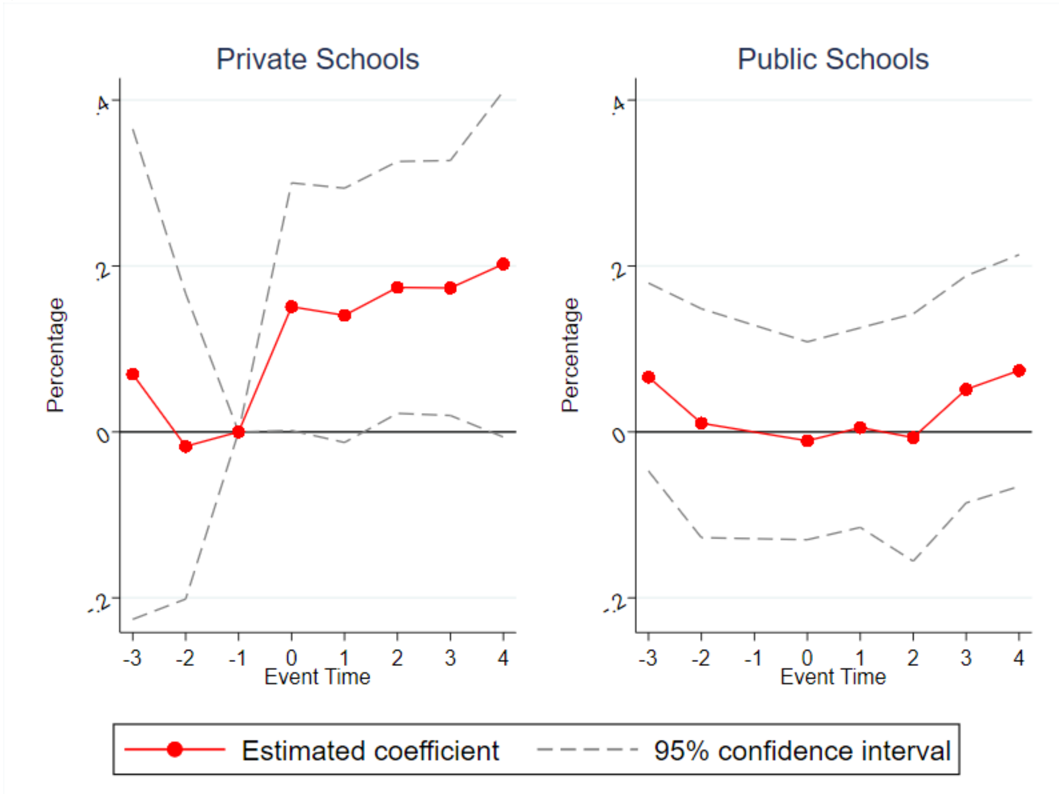
Notes: Sample includes a repeated cross-section of individuals between 5 and 16 years of age from a balanced district level panel of 14 treatment districts across 9 years of ASER data (2006-2014). The figure presents the effects of elite public colleges on dropout grade. $\tau = 0$ is the year of entry of elite public colleges. These estimates are average treatment effects of elite public colleges relative to the year before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2009, the ASER surveys conduced in 2006, 2007, 2008, 2009, 2010, 2011, 2012, and 2013 are denoted as $\tau = -3$, $\tau = -2$, $\tau = -1$, $\tau = 0$, $\tau = 1$, $\tau = 2$, $\tau = 3$ and $\tau = 4$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects. 95% confidence intervals are presented, standard errors are clustered at the district level.

Figure A.24: Impact of Elite Public Colleges on Dropouts in Primary School (Age 5-16)



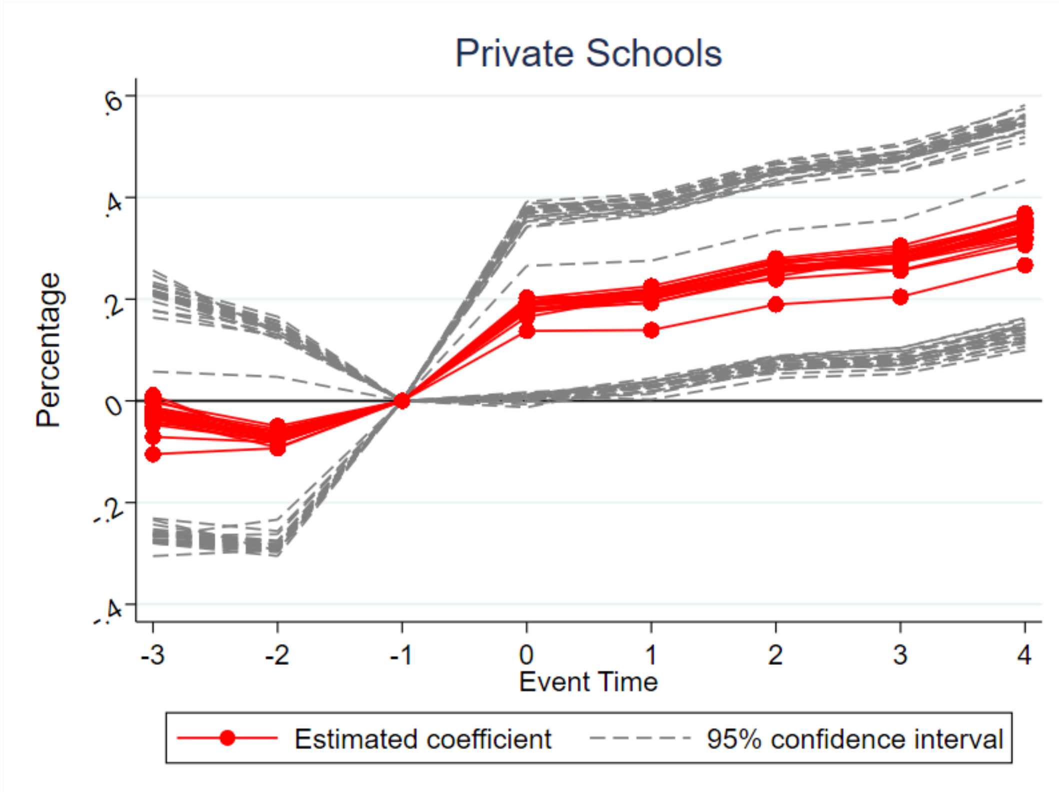
Notes: Sample includes a repeated cross-section of individuals between 5 and 16 years of age from a balanced district level panel of 14 treatment districts across 9 years of ASER data (2006-2014). The figure presents the effects of elite public colleges on the likelihood of dropping out in primary school (0/1). $\tau = 0$ is the year of entry of elite public colleges. These estimates are average treatment effects of elite public colleges relative to the year before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2009, the ASER surveys conduced in 2006, 2007, 2008, 2009, 2010, 2011, 2012, and 2013 are denoted as $\tau = -3$, $\tau = -2$, $\tau = -1$, $\tau = 0$, $\tau = 1$, $\tau = 2$, $\tau = 3$ and $\tau = 4$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects. 95% confidence intervals are presented, standard errors are clustered at the district level.

Figure A.25: Adding District-Specific Linear Trends: Impact of Elite Public Colleges on Private vs. Public Schools



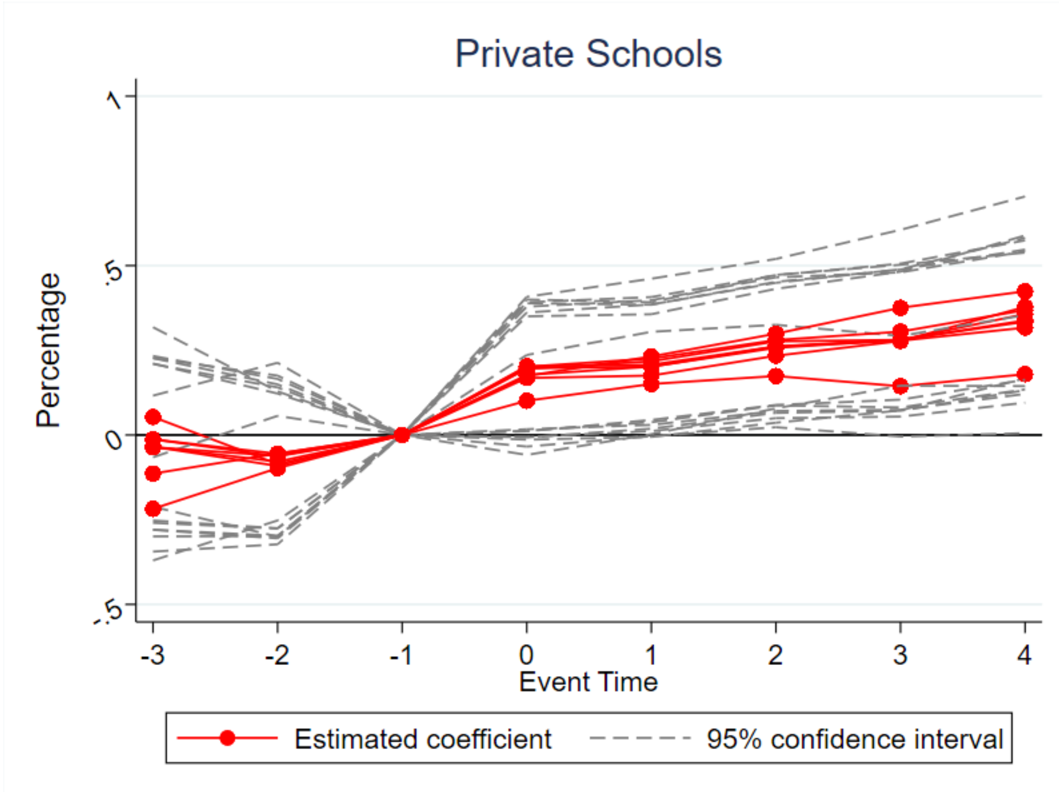
Notes: Sample includes a balanced district level panel of 23 treatment districts across 11 years of DISE data (2004-2014). The figure presents the effects of elite public colleges on number of private and public schools (natural logarithm). $\tau = 0$ is the year of entry of elite public colleges. These estimates are average treatment effects of elite public colleges relative to the year before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2007, the DISE surveys conduced in 2004, 2005, 2006, 2007, 2008, 2009, 2010, and 2011 are denoted as $\tau = -3$, $\tau = -2$, $\tau = -1$, $\tau = 0$, $\tau = 1$, $\tau = 2$, $\tau = 3$ and $\tau = 4$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects as well as district-specific linear trends. 95% confidence intervals are presented, standard errors are clustered at the district level.

Figure A.26: Dropping Each District: Impact of Elite Public Colleges on Private Schools



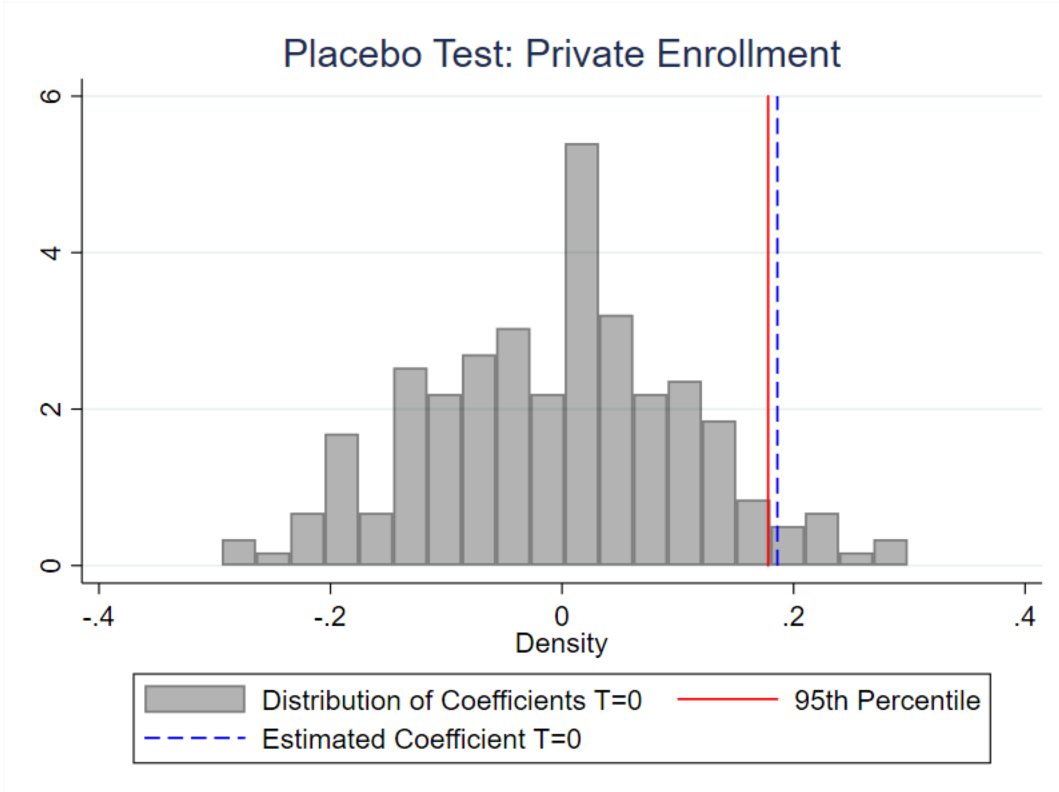
Notes: Sample includes a balanced district level panel of 23 treatment districts across 11 years of DISE data (2004-2014). The figure presents the effects of elite public colleges on number of private schools (natural logarithm). The figure presents results from 23 regressions, each time dropping one treatment district. $\tau = 0$ is the year of entry of elite public colleges. These estimates are average treatment effects of elite public colleges relative to the year before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2007, the DISE surveys conduced in 2004, 2005, 2006, 2007, 2008, 2009, 2010, and 2011 are denoted as $\tau = -3$, $\tau = -2$, $\tau = -1$, $\tau = 0$, $\tau = 1$, $\tau = 2$, $\tau = 3$ and $\tau = 4$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects. 95% confidence intervals are presented, standard errors are clustered at the district level.

Figure A.27: Dropping all Year-Specific Districts: Impact of Elite Public Colleges on Private Schools



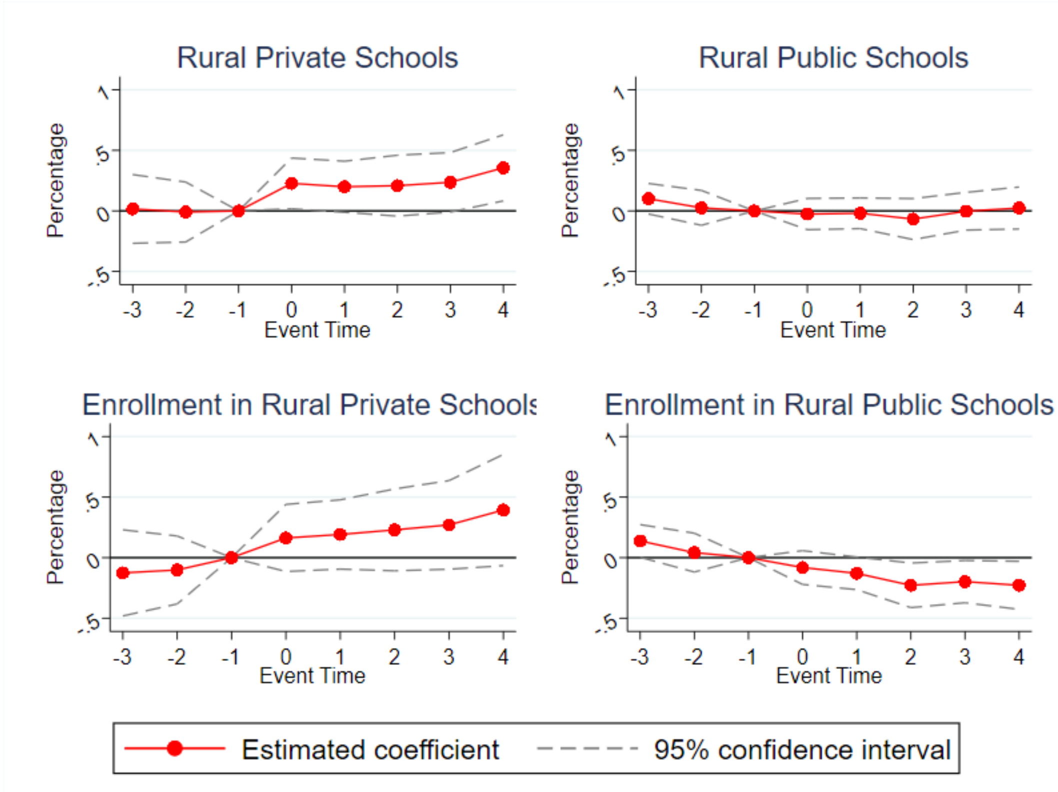
Notes: Sample includes a balanced district level panel of 23 treatment districts across 11 years of DISE data (2004-2014). The figure presents the effects of elite public colleges on number of private schools (natural logarithm). The figure presents results from 7 regressions, each time dropping all treatment districts that received an elite public college in a specific year. $\tau = 0$ is the year of entry of elite public colleges. These estimates are average treatment effects of elite public colleges relative to the year before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2007, the DISE surveys conduced in 2004, 2005, 2006, 2007, 2008, 2009, 2010, and 2011 are denoted as $\tau = -3$, $\tau = -2$, $\tau = -1$, $\tau = 0$, $\tau = 1$, $\tau = 2$, $\tau = 3$ and $\tau = 4$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects. 95% confidence intervals are presented, standard errors are clustered at the district level.

Figure A.28: Placebo Test: Impact of Elite Public Colleges on Private Schools at $T = 0$



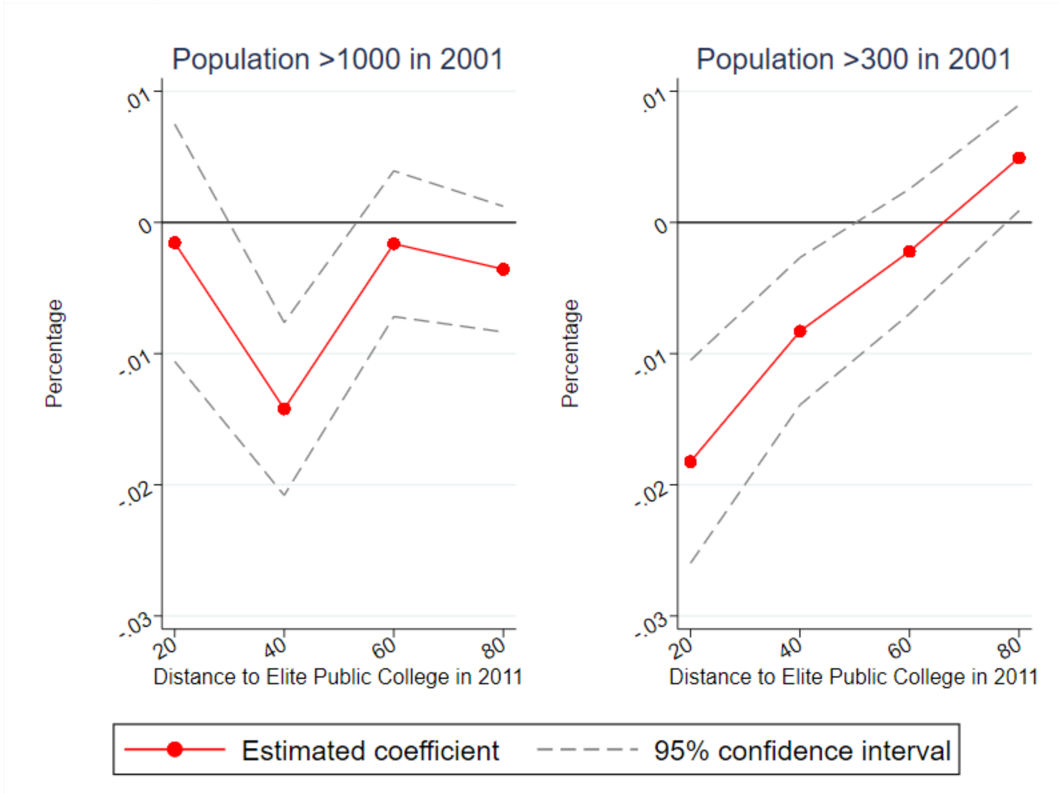
Notes: Sample includes a balanced district level panel of 23 treatment districts across 11 years of DISE data (2004-2014). The figure presents the distribution of the (placebo) estimates of the effects of elite public colleges on the number of private schools (natural logarithm) at $\tau = 0$ or year of entry of elite public colleges, when the year of entry is randomly assigned amongst treated districts. That is, it presents the distribution of estimates at $\tau = 0$ from 200 regressions, randomly assigning the year of entry of elite public colleges among treatment districts each time. Regressions includes district and year (round) fixed effects. The blue dashed line denotes the observed effect size at $\tau = 0$ from the baseline regression, and the solid red line indicates the 95% percentile of the distribution of the placebo estimates.

Figure A.29: Rural Schools and Enrollment: Impact of Elite Public Colleges on Private vs. Public Schools and Private vs. Public Enrollment



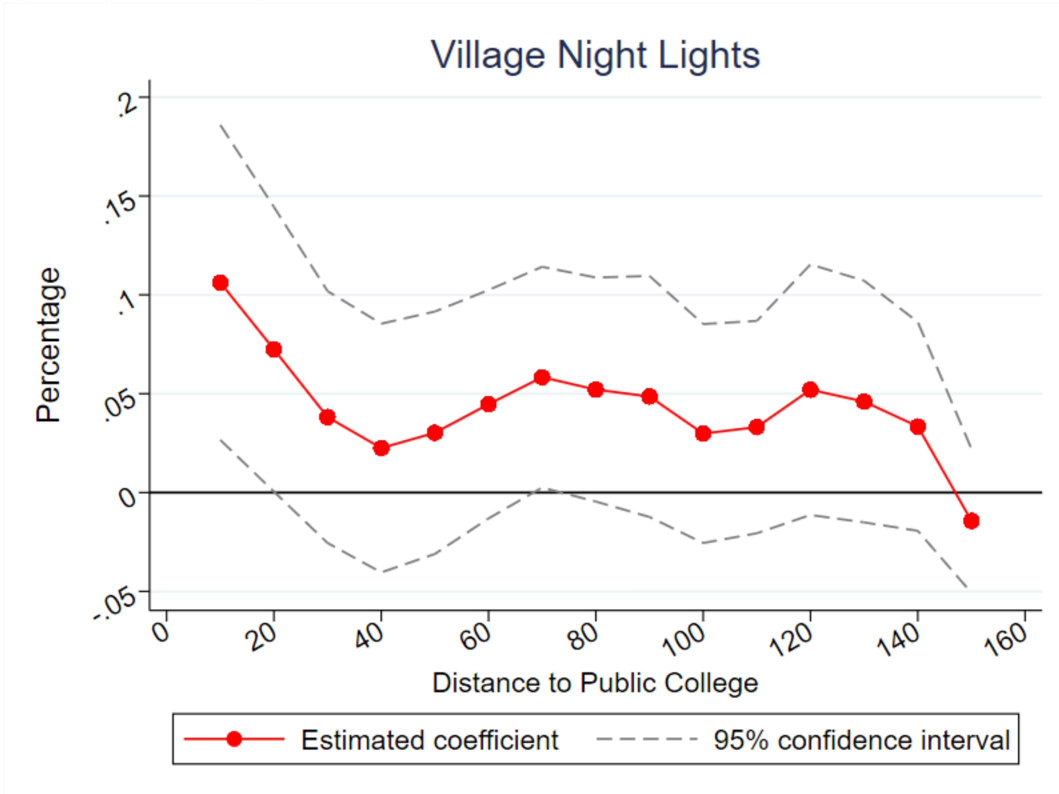
Notes: Sample includes a balanced district level panel of 23 treatment districts across 11 years of DISE data (2004-2014). The figure presents the effects of elite public colleges on number of rural private schools [top left], rural public schools [top right], enrollment in rural private schools [bottom left], and rural public schools [bottom right] (natural logarithm). $\tau = 0$ is the year of entry of elite public colleges. These estimates are average treatment effects of elite public colleges relative to the year before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2007, the DISE surveys conduced in 2004, 2005, 2006, 2007, 2008, 2009, 2010, and 2011 are denoted as $\tau = -3$, $\tau = -2$, $\tau = -1$, $\tau = 0$, $\tau = 1$, $\tau = 2$, $\tau = 3$ and $\tau = 4$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects as well as district-specific linear trends. 95% confidence intervals are presented, standard errors are clustered at the district level.

Figure A.30: Relationship between Village Population and Presence of Elite Public Colleges



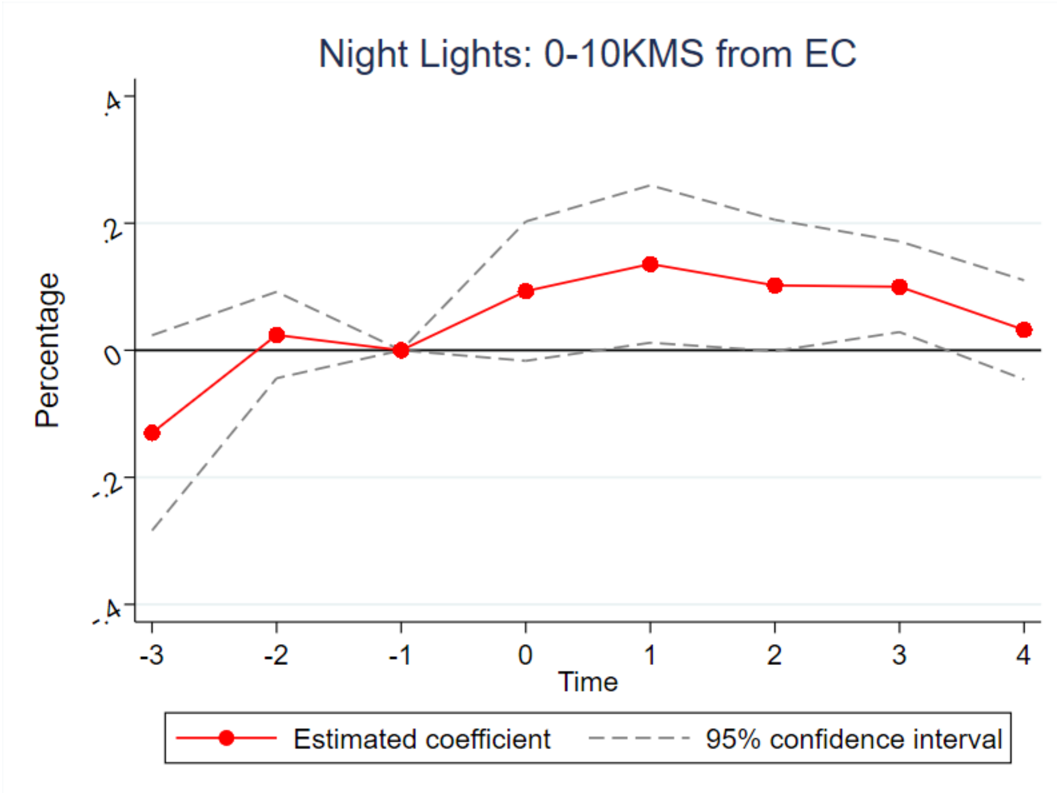
Notes: Sample includes a balanced panel of 489,576 villages across 3 Census Village Directories (1991, 2001 and 2011). The figure presents the relationship between village-specific distance to the nearest elite public college in 2011 and village population in 2001, or more specifically, whether the village population in 2001 was above the eligibility cut off for two government public infrastructure initiatives launched between 2001 and 2011: PMGSY (villages with population above 1000 were eligible, 0/1) and 300 (villages with population above 300 were eligible, 0/1). The regression includes district fixed effects. The variables on the X-axis are indicator variables (0/1) that denote if the village is less than 20, 40, 60 and 80 kms away from the nearest elite public college in 2011. 95% confidence intervals are presented, standard errors are heteroskedasticity-robust.

Figure A.31: State-by-Year FE: Impact of Elite Public Colleges on Village Level Night Light Intensity



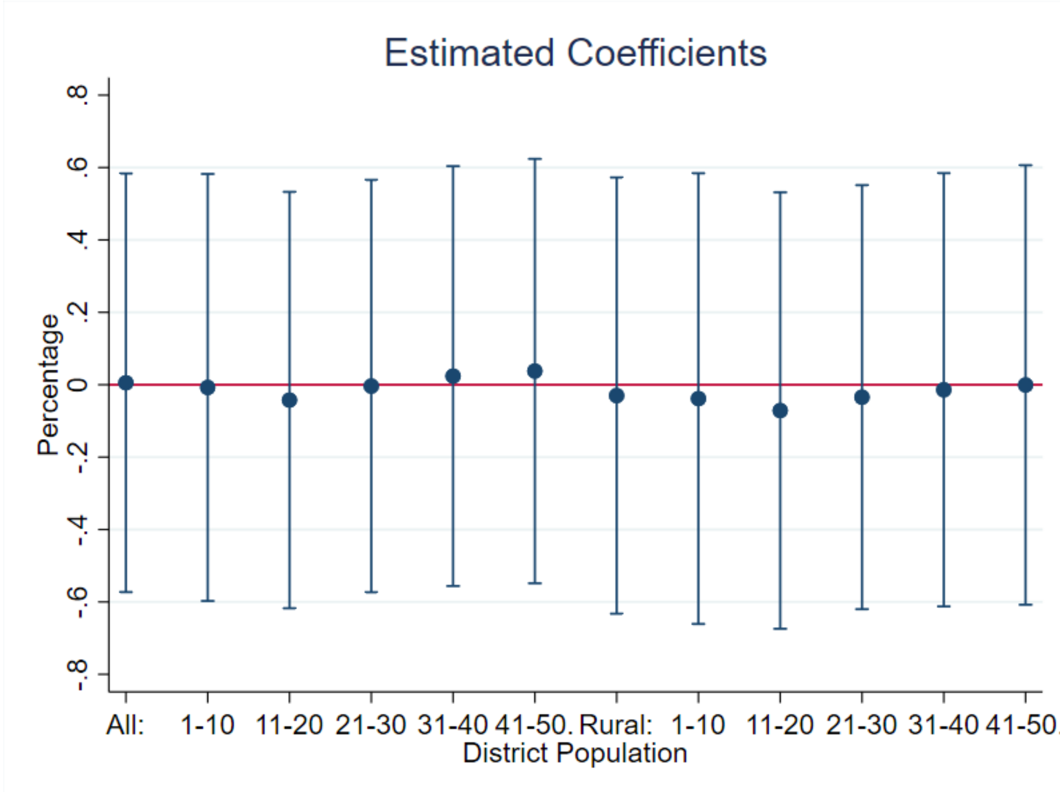
Notes: Sample includes a balanced panel of 453,921 villages across 9 years of nighttime lights data (2004-2012). The figure presents the difference-in-difference estimates of the effects of year-by-year changes in village-specific distance to the nearest elite public college, due to the entry of new elite public colleges between 2004 and 2012, on year-by-year changes in village level night lights (natural logarithm), a proxy for rural electrification. The regression, equation 2.4, includes village and state-by-year fixed effects. 95% confidence intervals are presented, standard errors are clustered at the district level.

Figure A.32: Event Study Specification: Impact of Elite Public Colleges on Village Level Night Light Intensity



Notes: Sample includes a balanced panel of 453,921 villages across 9 years of nighttime lights data (2004-2012). The figure presents the effects of elite public colleges on village level night lights (natural logarithm), a proxy for rural electrification, in villages within 10 km from the nearest elite public college in 2012. $\tau = 0$ is the year of entry of elite public colleges. These estimates are average treatment effects of elite public colleges relative to the year before elite public colleges were established ($\tau = -1$). For instance, if the treatment village came within 10 km of a new elite public college in 2007, the DISE surveys conduced in 2004, 2005, 2006, 2007, 2008, 2009, 2010, and 2011 are denoted as $\tau = -3$, $\tau = -2$, $\tau = -1$, $\tau = 0$, $\tau = 1$, $\tau = 2$, $\tau = 3$ and $\tau = 4$, respectively. The regression, equation 2.3, includes village and year fixed effects. 95% confidence intervals are presented, standard errors are clustered at the district level.

Figure A.33: Impact of Elite Public Colleges on Log Population by Age Group

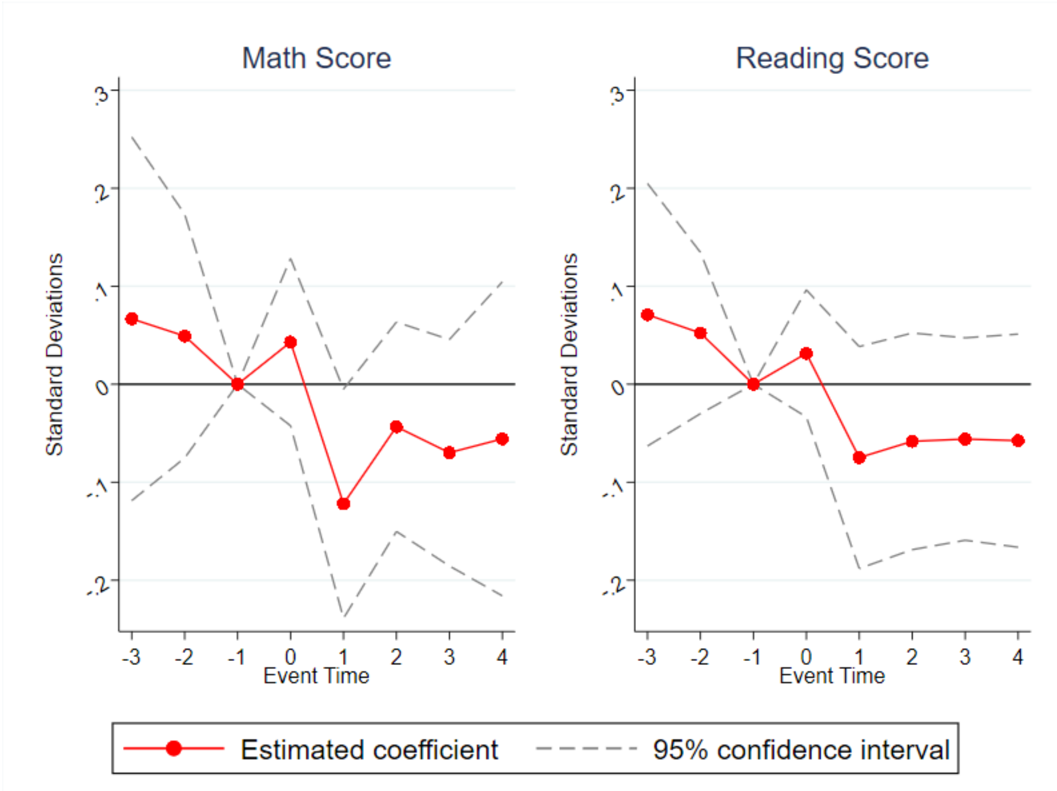


Notes: Sample includes a balanced district level panel of 25 treatment districts across 2 Census rounds (2001 and 2011). The figure presents difference in difference estimates of the effects of elite public colleges on district population, disaggregated by age group: 1-10, 11-20, 31-30, 31-40, 41-50. 95% confidence intervals are presented, standard errors are heteroskedasticity-robust.

Figure A.34: Impact of Elite Public Colleges on Wages

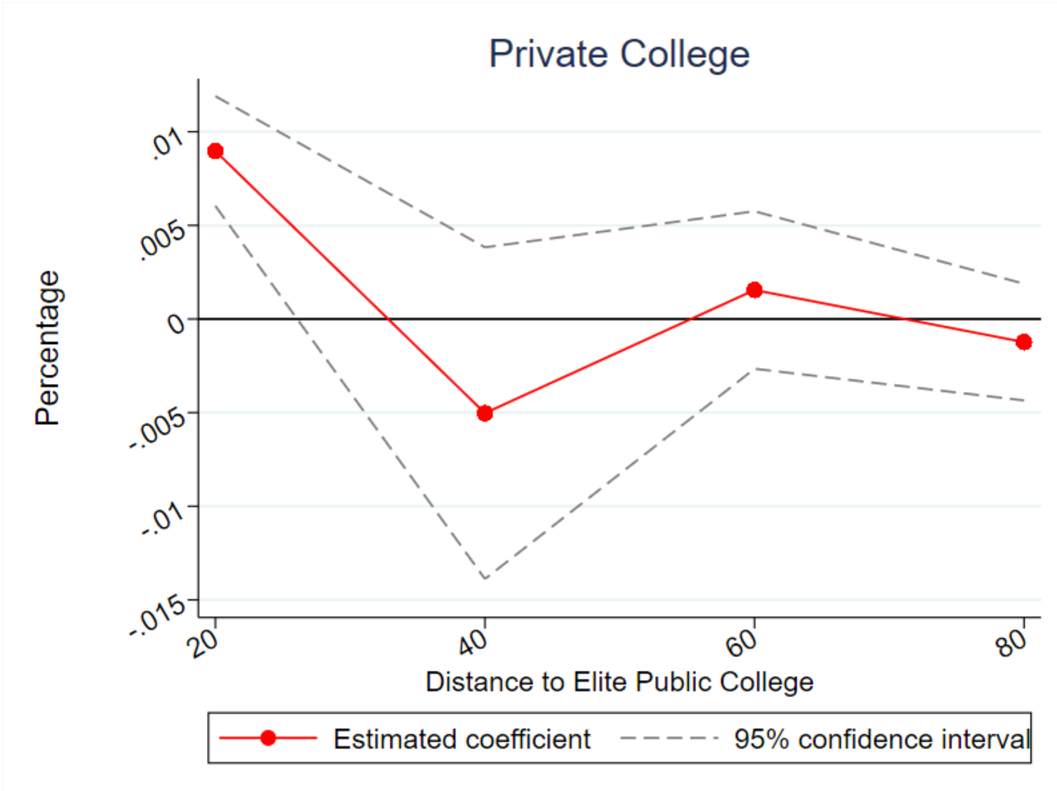
Notes: Sample includes a repeated cross-section of individuals from a balanced district level panel of 25 treatment districts across 4 NSS survey rounds (2004, 2007, 2010 and 2012). The figure presents the effects of elite public colleges on wages. $\tau = 0$ is the round of entry of elite public colleges. These are average treatment effects on treated districts of elite public colleges relative to the round before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2008, 2009 or 2010, the NSS surveys conduced in 2004, 2007, 2010, and 2012 are denoted as $\tau = -2$, $\tau = -1$, $\tau = 0$ and $\tau = 1$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects. 95% confidence interval is presented, standard errors are clustered at the district level.

Figure A.35: Impact of Elite Public Colleges on Test Scores (Age 5-16)



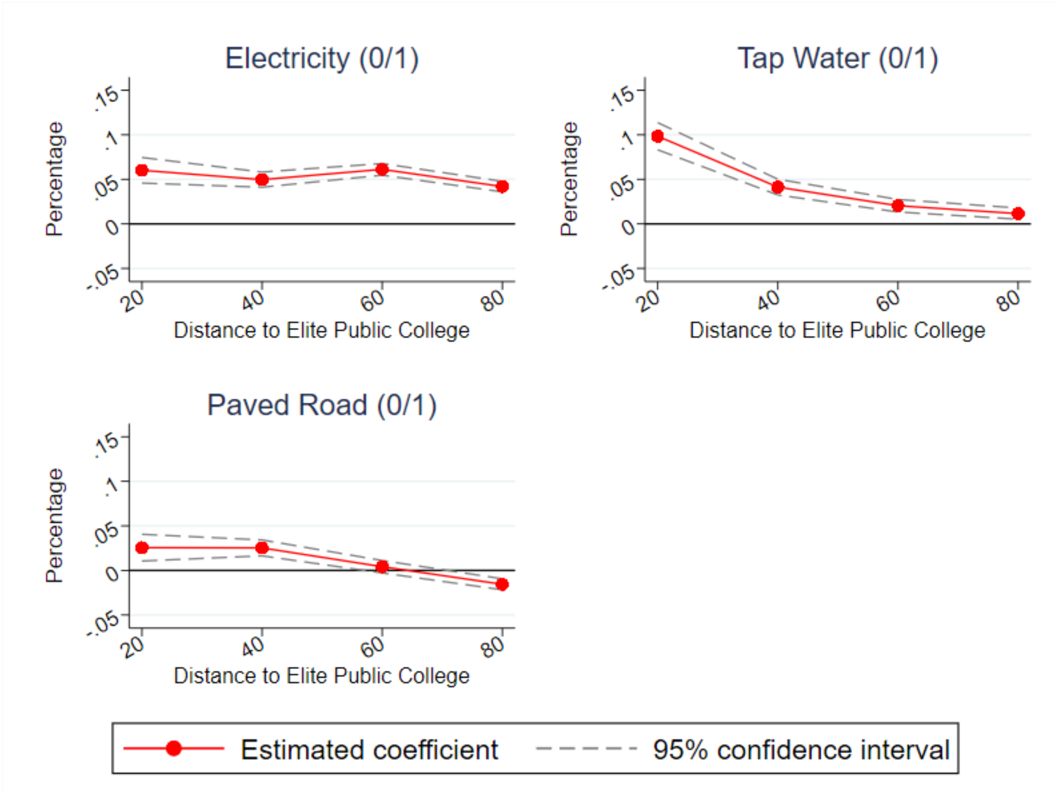
Notes: Sample includes a repeated cross-section of individuals between 5 and 16 years of age from a balanced district level panel of 14 treatment districts across 9 years of ASER data (2006-2014). The figure presents the effects of elite public colleges on math and reading test scores (in standard deviations). $\tau = 0$ is the year of entry of elite public colleges. These estimates are average treatment effects of elite public colleges relative to the year before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2009, the ASER surveys conduced in 2006, 2007, 2008, 2009, 2010, 2011, 2012, and 2013 are denoted as $\tau = -3$, $\tau = -2$, $\tau = -1$, $\tau = 0$, $\tau = 1$, $\tau = 2$, $\tau = 3$ and $\tau = 4$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects. 95% confidence intervals are presented, standard errors are clustered at the district level.

Figure A.36: Impact of Elite Public Colleges on Presence of Private College



Notes: Sample includes a balanced panel of 489,576 villages from the 2011 Census Village Directories. The figure presents the estimates of the relationship between village-specific distance to the nearest elite public college and presence of private college (0/1) in 2011. The regression includes district fixed effects. 95% confidence intervals are presented, standard errors are heteroskedasticity-robust.

Figure A.37: Dropping Districts Governed by 'Powerful' Politicians: Impact of Elite Public Colleges on Access to Electricity, Tap Water and Roads



Notes: Sample includes a balanced panel of 489,576 villages across 3 Census Village Directories (1991, 2001 and 2011). The figure presents the difference-in-difference estimates of the effects of change in village-specific distance to the nearest elite public college, due to the entry of new elite public colleges between 2001 and 2011, on the change in access to village level infrastructure (electricity (0/1), tap water (0/1), and paved roads (0/1)) between 2001 and 2011. The analysis sample drops districts governed by Members of Parliament (MPs) from the ruling coalition. In addition, the figure also presents placebo estimates of the effects of the change in village-specific distance to the nearest elite public college, due to the entry of new elite public colleges between 2001 and 2011, on the change in access to village level infrastructure between 1991 and 2001. The regression, equation 2.4, includes district and year (round) fixed effects, as well as indicator variables that denote if the village is less than 20, 40, 60 and 80 kms away from the nearest elite public college in 2011, respectively. 95% confidence intervals are presented, standard errors are heteroskedasticity-robust.

A.5 Tables

Table A.1: National Sample Survey (NSS): Summary Statistics on Years of Education and Educational Attainment (Age 6-20)

	Pooled	2004	2007	2010	2012
Years of Education	5.83	5.34	5.87	6.08	6.16
	(3.32)	(3.24)	(3.40)	(3.22)	(3.34)
Primary (0/1)	0.63	0.58	0.63	0.67	0.65
	(0.48)	(0.49)	(0.48)	(0.47)	(0.48)
Middle (0/1)	0.39	0.34	0.40	0.42	0.42
	(0.49)	(0.47)	(0.49)	(0.49)	(0.49)
Secondary (0/1)	0.19	0.15	0.20	0.21	0.23
	(0.40)	(0.35)	(0.40)	(0.41)	(0.42)
High School (0/1)	0.08	0.05	0.09	0.08	0.09
	(0.27)	(0.23)	(0.28)	(0.27)	(0.29)
Observations	41151	11363	11305	9330	9153

Notes: Sample includes a repeated cross-section of individuals between 6 and 20 years of age from a balanced district level panel of 25 treatment districts across 4 NSS survey rounds (2004, 2007, 2010 and 2012). The table presents the mean and standard deviation (in parentheses) for years of schooling and educational attainment in treatment districts.

Table A.2: Annual Survey of Education Report (ASER): Summary Statistics on Public vs. Private Enrollment (Age 6-16)

	Pooled	2006	2007	2008	2009
Public Enrollment (0/1)	0.57	0.61	0.61	0.60	0.61
	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)
Private Enrollment (0/1)	0.32	0.25	0.29	0.30	0.27
	(0.47)	(0.43)	(0.45)	(0.46)	(0.45)
Observations	120915	15774	15705	14371	13750

Notes: Sample includes a repeated cross-section of individuals between 5 and 16 years of age from a balanced district level panel of 14 treatment districts across 9 years of ASER data (2006-2014). The table presents the mean and standard deviation (in parentheses) for private and public enrollment status in treatment districts.

Table A.3: Annual Survey of Education Report (ASER): Summary Statistics on Public vs. Private Enrollment (Age 6-16)

	2010	2011	2012	2013	2014
Public Enrollment (0/1)	0.57	0.55	0.53	0.51	0.50
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Private Enrollment (0/1)	0.33	0.35	0.36	0.39	0.40
	(0.47)	(0.48)	(0.48)	(0.49)	(0.49)
Observations	13955	13145	12161	11346	10708

Notes: Sample includes a repeated cross-section of individuals between 5 and 16 years of age from a balanced district level panel of 14 treatment districts across 9 years of ASER data (2006-2014). The table presents the mean and standard deviation (in parentheses) for private and public enrollment status in treatment districts.

Table A.4: District Information System for Education (DISE): Summary Statistics on # of Private and Public Schools

	All	2004	2005	2006	2007	2008
# Private Schools (00s)	5.41	3.49	3.84	4.48	5.04	5.36
	(4.95)	(3.55)	(4.06)	(4.47)	(4.78)	(5.11)
# Public Schools (00s)	16.91	15.55	16.52	16.82	17.06	16.77
	(13.30)	(12.72)	(13.61)	(14.47)	(14.11)	(13.56)
Observations	253	23	23	23	23	23

Notes: Sample includes a balanced district level panel of 23 treatment districts across 11 years of DISE data (2004-2014).The table presents the mean and standard deviation (in parentheses) for number of private and public schools in treatment districts.

Table A.5: District Information System for Education (DISE): Summary Statistics on # of Private and Public Schools

	2009	2010	2011	2012	2013	2014
# Private Schools (00s)	5.69	5.72	5.97	6.33	6.67	6.93
	(5.41)	(4.90)	(4.93)	(5.24)	(5.62)	(5.78)
# Public Schools (00s)	16.86	17.16	17.16	17.47	17.54	17.12
	(13.63)	(13.37)	(13.25)	(13.38)	(13.94)	(13.10)
Observations	23	23	23	23	23	23

Notes: Sample includes a balanced district level panel of 23 treatment districts across 11 years of DISE data (2004-2014).The table presents the mean and standard deviation (in parentheses) for number of private and public schools in treatment districts.

Table A.6: Cluster-Bootstrap P-Values: Impact of Elite Public Colleges on Years of Schooling and Educational Attainment

	(1) Years of Education β / SE	(2) Primary β / SE	(3) Middle β / SE	(4) Secondary β / SE	(5) High School β / SE
T= -2.0000	0.098	0.018	0.004	0.001	-0.000
	(0.58)	(0.58)	(0.86)	(1.00)	(1.00)
T= 0.0000	0.277	0.049	0.046	0.021	0.011
	(0.02)	(0.00)	(0.24)	(0.18)	(0.30)
T= 1.0000	0.810	0.099	0.133	0.079	0.053
	(0.00)	(0.00)	(0.00)	(0.00)	(0.14)
Observations	41124	41151	41151	41151	41151

Notes: Notes: Sample includes a repeated cross-section of individuals between 6 and 20 years of age from a balanced district level panel of 25 treatment districts across 4 NSS survey rounds (2004, 2007, 2010 and 2012). The table presents the effects of elite public colleges on years of schooling. $\tau = 0$ is the round of entry of elite public colleges. These are average treatment effects on treated districts of elite public colleges relative to the round before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2008, 2009 or 2010, the NSS surveys conduced in 2004, 2007, 2010, and 2012 are denoted as $\tau = -2$, $\tau = -1$, $\tau = 0$ and $\tau = 1$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects. Standard errors are clustered by district (100 replications). P-values are in parentheses.

Table A.7: Cluster-Bootstrap P-Values: Impact of Elite Public Colleges on on Private vs. Public Enrollment (Age 5-16)

	(1) Public Enrollment β / SE	(2) Private Enrollment β / SE
T = -3	-0.025	0.018
	(0.60)	(0.64)
T = -2	0.005	0.008
	(0.94)	(0.84)
T = 0	-0.049	0.043
	(0.06)	(0.04)
T = 1	-0.096	0.080
	(0.06)	(0.02)
T = 2	-0.097	0.101
	(0.02)	(0.00)
T = 3	-0.079	0.078
	(0.02)	(0.02)
T = 4	-0.135	0.129
	(0.02)	(0.00)
Observations	120915	120915

Notes: Notes: Sample includes a repeated cross-section of individuals between 5 and 16 years of age from a balanced district level panel of 14 treatment districts across 9 years of ASER data (2006-2014). The table presents the effects of elite public colleges on private school (0/1) vs. public school (0/1) enrollment status. $\tau = 0$ is the year of entry of elite public colleges. These estimates are average treatment effects of elite public colleges relative to the year before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2009, the ASER surveys conduced in 2006, 2007, 2008, 2009, 2010, 2011, 2012, and 2013 are denoted as $\tau = -3$, $\tau = -2$, $\tau = -1$, $\tau = 0$, $\tau = 1$, $\tau = 2$, $\tau = 3$ and $\tau = 4$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects. Standard errors are clustered by district (100 replications). P-values are in parentheses.

Table A.8: Cluster-Bootstrap P-Values: Impact of Elite Public Colleges on on Private vs. Public Schools

	(1) Private Schools β / SE	(2) Public Schools β / SE
T = -3	-0.029	0.066
	(0.90)	(0.34)
T = -2	-0.072	0.010
	(0.12)	(0.54)
T = 0	0.186	-0.011
	(0.00)	(0.86)
T = 1	0.205	0.005
	(0.00)	(0.82)
T = 2	0.258	-0.007
	(0.00)	(1.00)
T = 3	0.277	0.051
	(0.00)	(0.22)
T = 4	0.337	0.074
	(0.00)	(0.24)
Observations	253	253

Notes: Notes: Sample includes a balanced district level panel of 23 treatment districts across 11 years of DISE data (2004-2014). The figure presents the effects of elite public colleges on number of private and public schools (natural logarithm). $\tau = 0$ is the year of entry of elite public colleges. These estimates are average treatment effects of elite public colleges relative to the year before elite public colleges were established ($\tau = -1$). For instance, if the treatment district received a new elite public college in 2007, the DISE surveys conduced in 2004, 2005, 2006, 2007, 2008, 2009, 2010, and 2011 are denoted as $\tau = -3$, $\tau = -2$, $\tau = -1$, $\tau = 0$, $\tau = 1$, $\tau = 2$, $\tau = 3$ and $\tau = 4$, respectively. The regression, equation 2.3, includes district and year (round) fixed effects. Standard errors are clustered by district (100 replications). P-values are in parentheses.

Appendix B

Chapter 2 of appendix

B.1 Appendix: Data

China Health and Nutrition Survey (CHNS)

The CHNS is collected by the Carolina Population Center at the University of North Carolina at Chapel Hill and the National Institute for Nutrition and Health (NINH). This survey includes subjects from a sample of about 7,200 households with over 30,000 individuals in 15 provinces and municipal cities in China from 1989 to 2011.[1] Although the CHNS sample is not representative of the Chinese population, one-third of the Chinese population (approximately 450 million people in 1989) lives in these provinces. The CHNS has released eight waves of data so far (1989, 1991, 1993, 1997, 2000, 2004, 2006, and 2009). I use

[1]Figure B.16 presents the provinces in CHNS. A detailed description of the CHNS design can be found at www.cpc.unc.edu/projects/china. I am grateful to Teevrat Garg and Matthew Gibson for sharing the CHNS data with county identifiers.

the 2004-2009 data waves of the survey because the earlier waves did not collect children's time use data. Following ITUS, I restricted analyses to school-age children, individuals over 5 but less than 17 years of age. Unlike ITUS, CHNS did not collect time use data for a particular date. Children were asked about the time spent on sleep on a 'usual' or 'typical' day. Similarly, children were asked about time spent on leisure activities, both physical (running, soccer, etc.) and sedentary (TV, video games, etc.) in nature, as well as on homework. Data on leisure and homework was collected for both weekdays and weekends. Although measures for leisure and study are not comparable to ITUS, the direction of the estimates would still be useful as corroborative evidence.

Rural Economic and Demographic Survey (REDS)

I use village- and household-level surveys from the 2006 round of REDS, administered by the National Council of Applied Economic Research (NCAER). It is a nationally representative survey of rural households in India spanning over 200 villages across 100 districts in 17 major states.[2] The REDS data provide village identifiers. Therefore, I compute sunset times at the village level. Like ITUS and DHS, I restrict the REDS sample to children between 6 and 16 years of age.[3] Roughly 90% school-age children are enrolled in school; 52% have completed primary school and 23% have completed middle school. In the previous 50 years, the average village observed 7 episodes of in-migration and 2 episodes of out-migration. In the average village 40% households have an electricity connection, and roughly 20% households have access to running water. The REDS

[2]REDS villages are mapped in Figure B.17. I am grateful to Andrew Foster and NCAER for sharing the REDS secure data set with village identifiers.

[3]Table B.6 presents summary statistics for outcomes of interest, while Table B.7 describes the REDS villages.

data also include record of the prevailing village-level daily wage rate for children and gender-specific daily wage rate for adults.

Young Lives Survey (YLS)

Young Lives Survey (YLS) is a study of childhood poverty coordinated by the University of Oxford.[4] The study has collected data on two cohorts of children in the state of Andhra Pradesh, in India: 1,008 children born between January 1994 and June 1995, and 2,011 children born between January 2001 and June 2002.[5] Data were collected from children and their families using household visits in 2002, 2006, 2009, and in 2013. Children were tested in math across these survey rounds. The tests were related to the formal school curriculum in Andhra Pradesh. Different tests were administered to children across rounds in order to ensure that they were appropriate for the children's age and current stage of education. These tests were quite comprehensive, with the math questionnaire containing 30 questions.

In addition, in 2011, the Young Lives study visited a random sub-set of schools attended by children in the younger cohort to conduct school-level data. I use data on school start times and school-level test scores in Science, Math, Social Studies, Telugu, Hindi and English to investigate the mitigative effects of later school start times on the sunset-education relationship.

[4]Young Lives is funded by UK aid from the Department for International Development (DFID). The views expressed here are those of the author(s). They are not necessarily those of Young Lives, the University of Oxford, DFID, or other funders. For more information of YLS, see: www.younglives.org.uk

[5]The districts included in the sample are presented in Figure B.18. Figure B.19 presents the distribution of annual average sunset time for all 7 districts in the YLS data as well as the distribution of sunset time at the district-test-date level.

Sunset Time

I use two measures of sunset time for my analysis: daily sunset time and annual average sunset time.

Daily Sunset: ITUS collects time use data for particular dates across a year for a cross-section of households in India. Therefore, to estimate the effects of sunset on time use in India, I examine how daily time use co-varies with seasonal variation in daily sunset time at the district level.

Seasonal variation in sunset time is highly correlated with seasonal variation in sunrise time and daylight duration; daily sunset time is positively correlated with daylight duration and negatively correlated with daily sunrise time. I focus on sunset time rather than sunrise time because of the link between sunset time and sleep as emphasized by the existing medical literature. Consistent with medical studies, I show later sunset delays bedtime but has no influence on wake-up time.

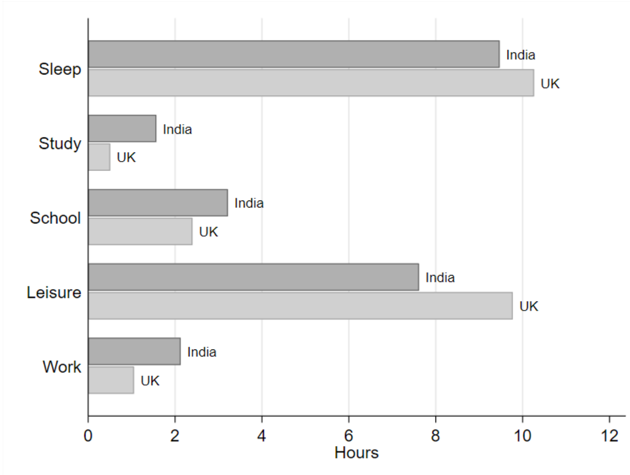
However, it is possible that daylight duration and not daily sunset time affects sleep through hedonic value of leisure or some other channel. I show that increase in leisure on later sunset days is largely driven by indoor and not outdoor leisure. Furthermore, because sunset time is equal to sunrise time plus hours of daylight, I control for sunrise time and daylight duration separately. I show the estimate of the effect of later sunset on sleep remains relatively unaffected, although it is not statistically significant, presumably because sunset time, sunrise time, and daylight duration are highly correlated (Table B.8).

Annual Average Sunset: First, unlike ITUS, CHNS collects data on time allocation for a 'typical' day of the year, and not for a particular date. Therefore, I corroborate the effects of sunset time on time use using a different type of variation: I examine how time use for cross-section of children in a particular location (district) on a 'usual' day co-varies with annual average sunset time. Second, I examine the effects of later sunset on stock indicators of education using DHS, REDS, and YLS data. I evaluate how children's education outcomes co-vary with annual average sunset time across the east-west gradient.

Annual average sunset is perfectly correlated with longitude, unless time zone boundaries break this link. In fact, I exploit this sharp discontinuity in annual average sunset time at the time zone border in Kalimantan, Indonesia, to corroborate education estimates from India. Importantly, because all locations in my analyses experience nearly the same average amount of daylight, daylight duration is not a confounder for estimates of the effects of annual average sunset on time use or education outcomes.

Lastly, annual average sunset time is orthogonal to latitude for countries in my analyses. But the amplitude of the variation in daily sunset time is perfectly correlated with latitude. If there exist non-linearities in the relationship between daily sunset time and sleep or sleep and education production, the interaction between annual average sunset and latitude may help inform policy interventions. In my analyses, however, I fail to find evidence for non-linearities in the relationship between sunset time and sleep and sunset time and education outcomes. It is important to note that I observe moderate values of sleep and sunset time in data from India, China, and Indonesia. It is possible that these relationships are highly non-linear at more extreme values of sleep and sunset time.

Figure B.1: Summary Statistics: Children's Time Use in India vs. United Kingdom



Notes: This figure compares children's (age 8 to 16) allocation of time to sleep, study, school, leisure and work between India and the United Kingdom (U.K.). I use the India Time Use Survey (ITUS) for India, and data from the Multinational Time Use Study (MTUS) for the U.K. Although MTUS provides time use data for a number of other countries, I include only the U.K. since the data for the U.K. was collected in 2000, which is only a year after ITUS, and because the U.K. wave includes data on children's time use.

Figure B.2: Districts in the India Time Use Survey (ITUS)

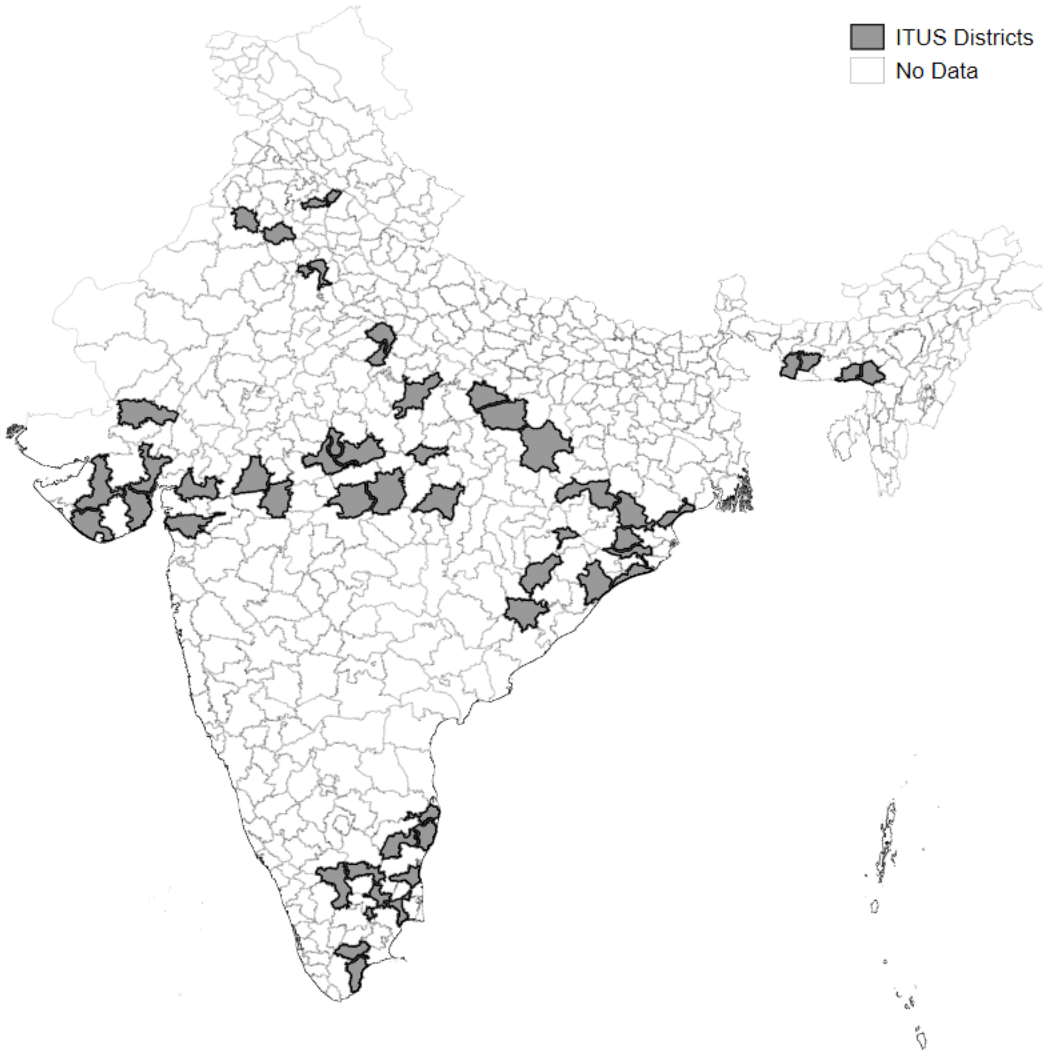
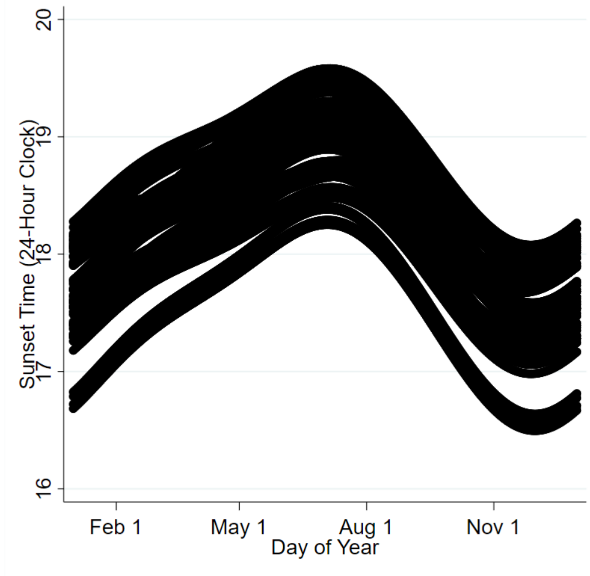
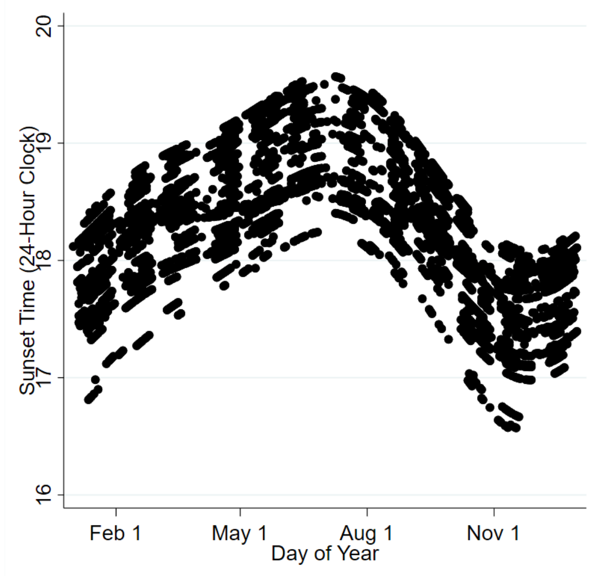


Figure B.3: Summary Statistics: Distribution of Daily Sunset Time in ITUS Districts



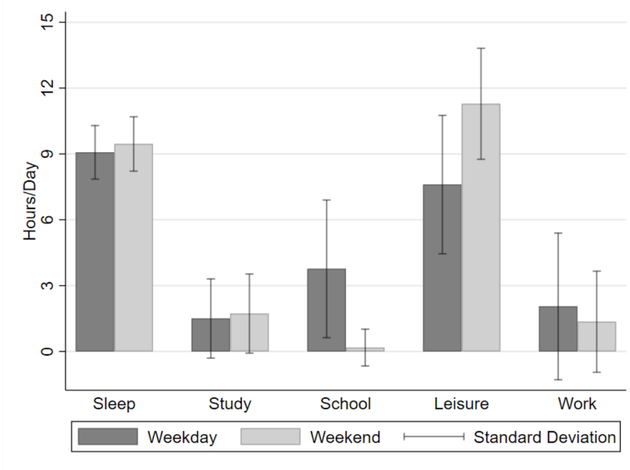
(a) Daily sunset time in ITUS districts



(b) Daily sunset time for sampled dates in ITUS districts

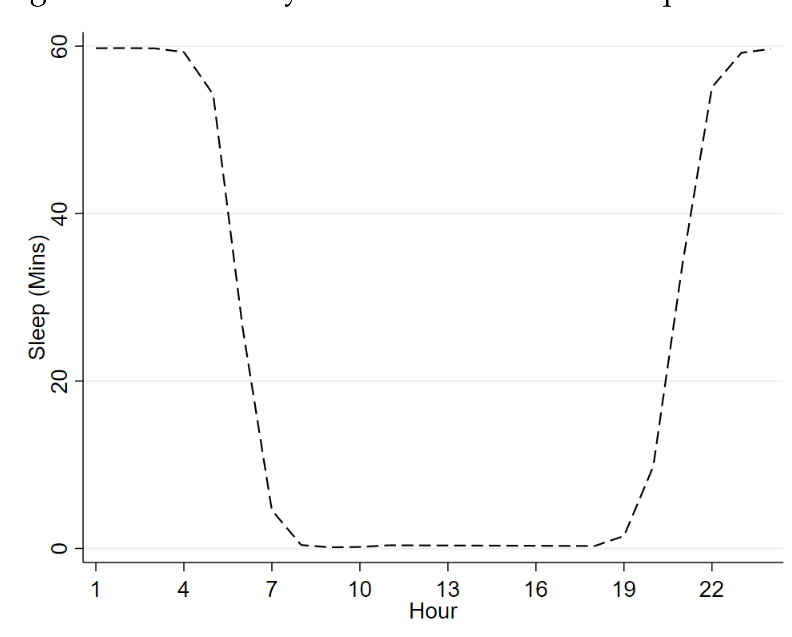
Notes: This figure presents distribution of daily sunset time in ITUS districts. Panel (a) presents daily sunset time for every day in a year for all districts in ITUS. Panel (b) presents daily sunset time for dates for which time use data was collected in ITUS districts.

Figure B.4: Summary Statistics: Children's Time Use



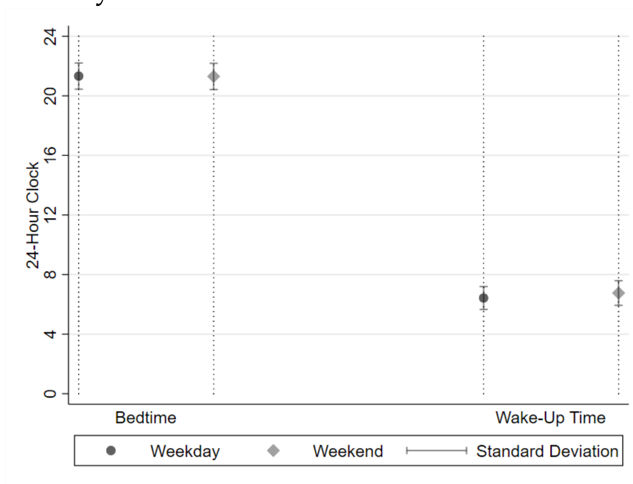
Notes: This figure presents the average time allocated by children between 6 and 16 years of age to sleep, study, school, leisure and work on weekdays and weekends in India. Source: ITUS.

Figure B.5: Summary Statistics: Children's Sleep Patterns



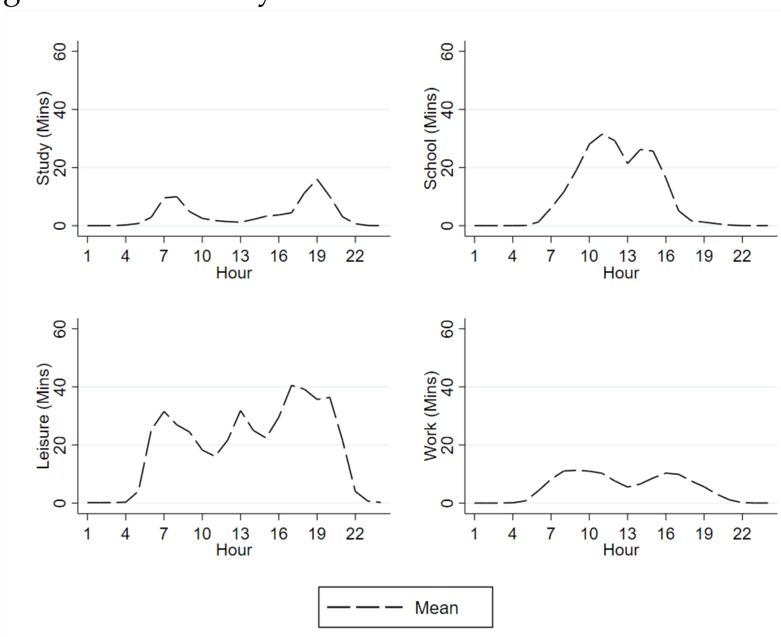
Notes: This figure presents the average time spent on sleep by children between 6 and 16 years of age for each hour of the 24-hour day cycle on a weekday in India. Source: ITUS.

Figure B.6: Summary Statistics: Children's Bedtimes and Wake-up Times



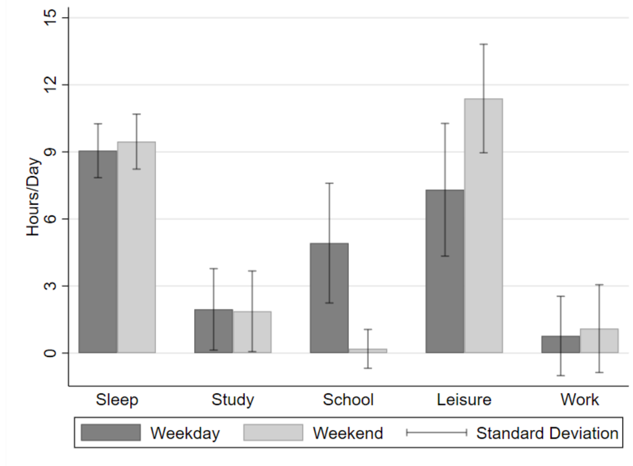
Notes: This figure presents the average bedtimes and wake-up times for children between 6 and 16 years of age on weekdays and weekends. Source: ITUS.

Figure B.7: Summary Statistics: Children's Time Use Patterns



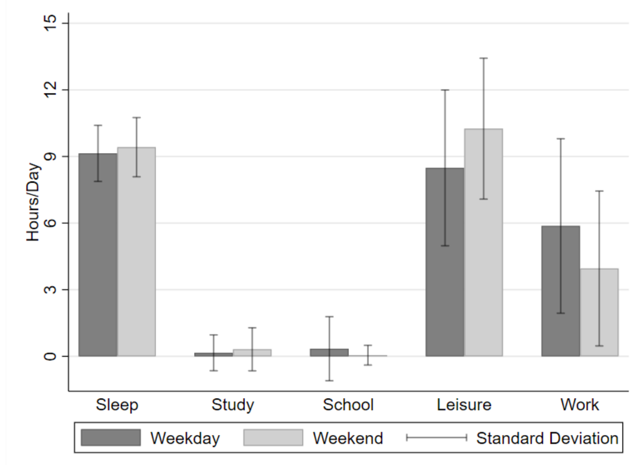
Notes: This figure presents the average time spent on study, school, leisure and work by children between 6 and 16 years of age for each hour of the 24-hour day cycle on a weekday in India. Source: ITUS.

Figure B.8: Summary Statistics: Students' Time Use



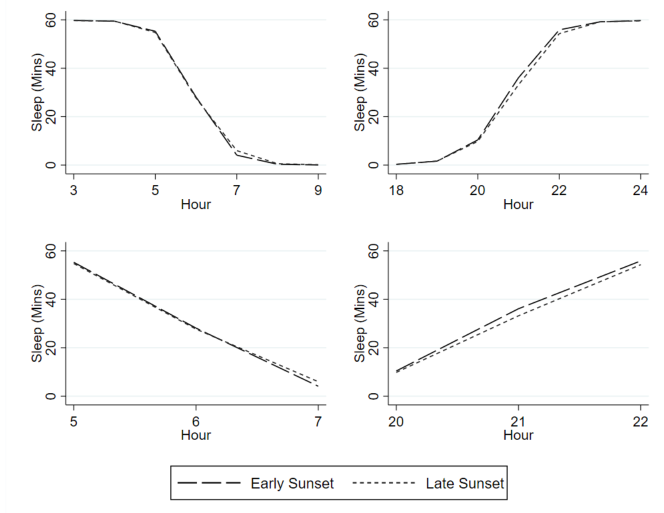
Notes: This figure presents the average time spent on sleep, study, school, leisure and work by students (or children whose primary activity is school) between 6 and 16 years of age on weekdays and weekends. Source: ITUS.

Figure B.9: Summary Statistics: Child Laborers' Time Use



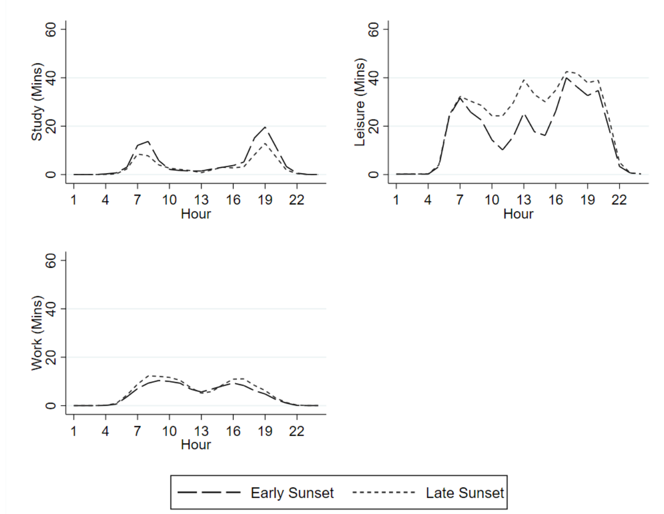
Notes: This figure presents the average time spent on sleep, study, school, leisure and work by child laborers (or children whose primary activity is work) between 6 and 16 years of age on weekdays and weekends. Source: ITUS.

Figure B.10: Children's Sleep Patterns by Early and Later Sunset Time



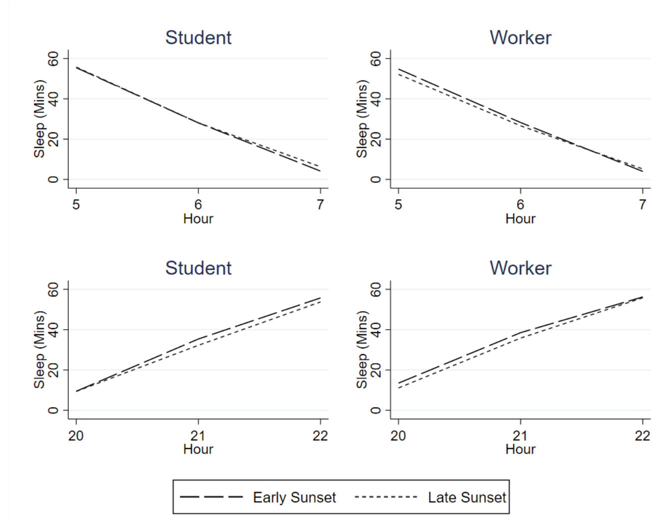
Notes: This figure compares the average time spent on sleep by children between 6 and 16 years of age for each hour across the 24-hour day cycle between early and late sunset days on a weekday. Within each district, early sunset observations include children interviewed when seasonal sunsets were below 25th percentile, while late sunset observations include children interviewed when seasonal sunsets were above 75th percentile. Source: ITUS.

Figure B.11: Children's Time Use Patterns by Early and Later Sunset Time



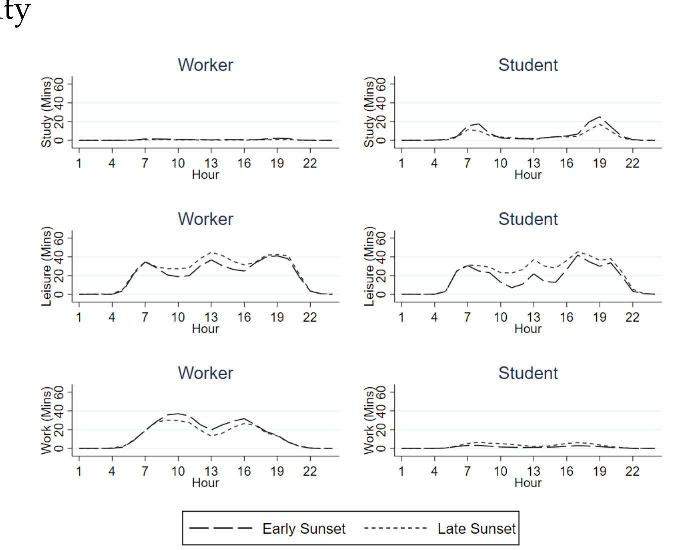
Notes: This figure compares the average time spent on study, school, leisure and work by children between 6 and 16 years of age for each hour across the 24-hour day cycle between early and late sunset days on a weekday. Within each district, early sunset observations include children interviewed when seasonal sunsets were below 25th percentile, while late sunset observations include children interviewed when seasonal sunsets were above 75th percentile. Source: ITUS.

Figure B.12: Children's Sleep Patterns by Early and Later Sunset Time by Primary Activity



Notes: This figure compares the average time spent on sleep by children between 6 and 16 years of age for each hour across the 24-hour day cycle between early and late sunset days on a weekday. Within each district, early sunset observations include children interviewed when seasonal sunsets were below 25th percentile, while late sunset observations include children interviewed when seasonal sunsets were above 75th percentile. Source: ITUS.

Figure B.13: Children's Time Use Patterns by Early and Later Sunset Time by Primary Activity



Notes: This figure compares the average time spent on study, leisure and work by children between 6 and 16 years of age for each hour across the 24-hour day cycle between early and late sunset days on a weekday. Within each district, early sunset observations include children interviewed when seasonal sunsets were below 25th percentile, while late sunset observations include children interviewed when seasonal sunsets were above 75th percentile. Source: ITUS.

Figure B.14: Primary Sampling Units (Villages/City Blocks) in the 2015 Indian DHS

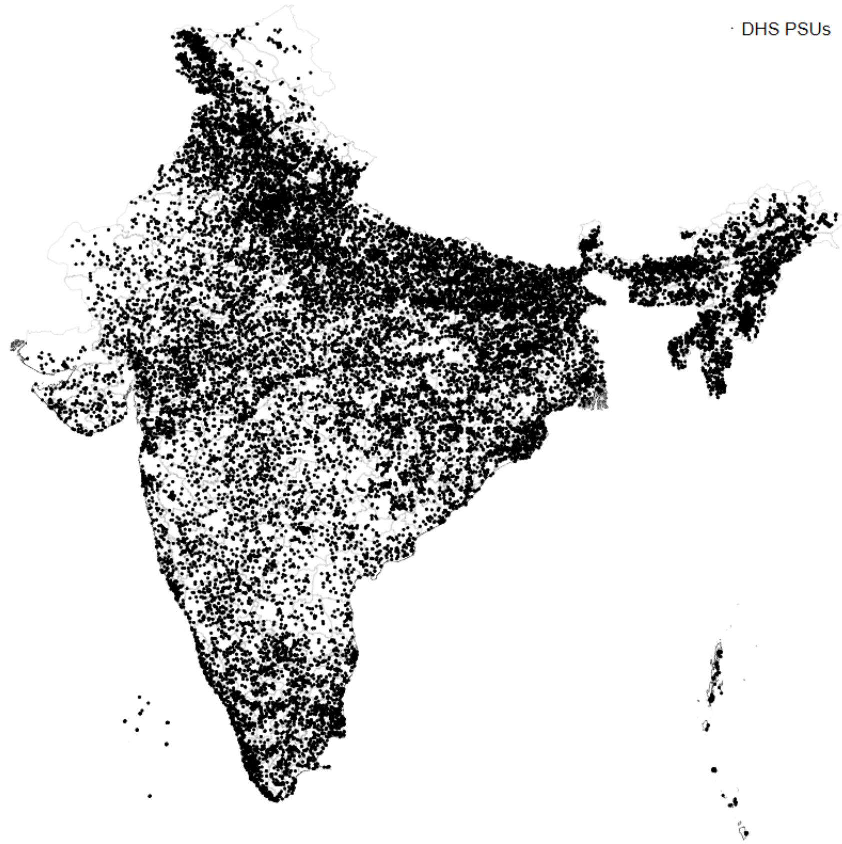


Figure B.15: Summary Statistics: Distribution of Annual Average Sunset Time at the Sampling Unit Level (Villages/City Blocks) in the 2015 Indian DHS

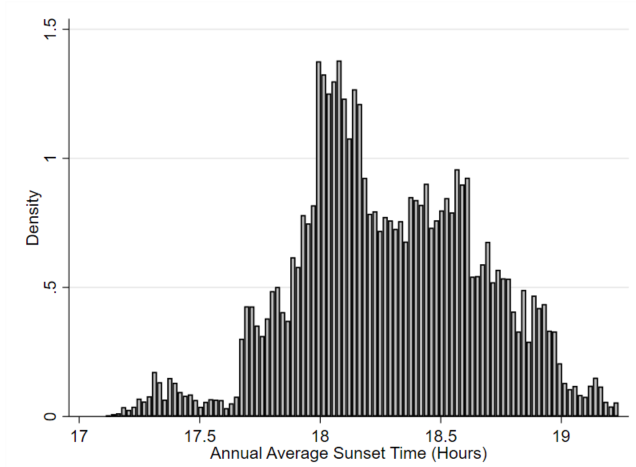


Figure B.16: Provinces in the China Health an Nutrition Survey (CHNS)

Figure B.17: Villages in Rural Economic and Demographic Survey (REDS)

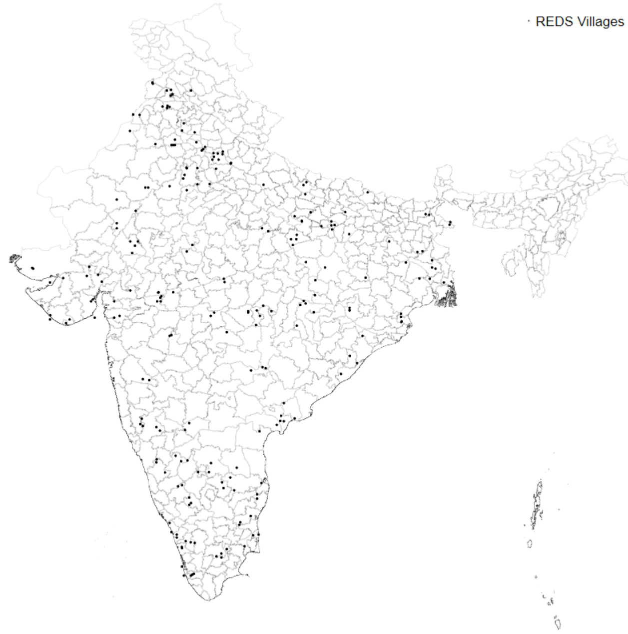


Figure B.18: Districts in the Young Lives Study (YLS)

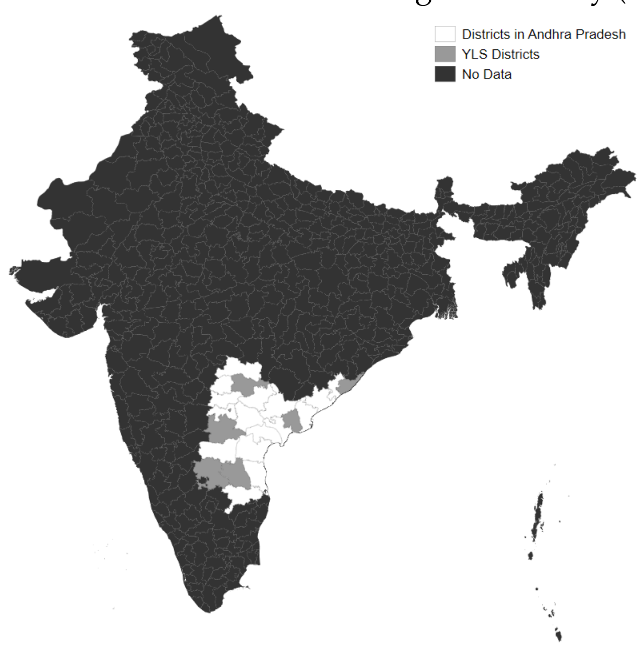
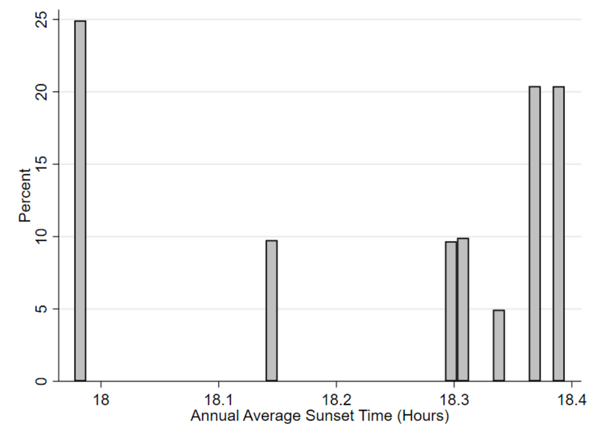
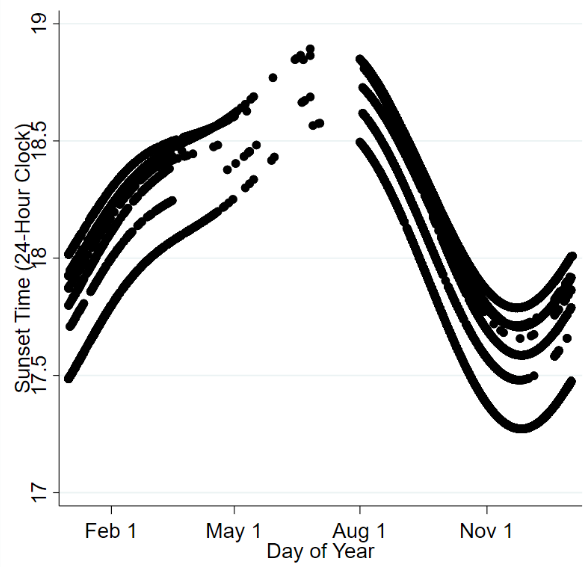


Figure B.19: Summary Statistics: Distribution of Annual Average Sunset Time and Day-of-Test Sunset Time in YLS Districts



(a) Distribution of Annual Average Sunset Time



(b) Distribution of Day-of-Test Sunset Time

Notes: This figure presents distribution of annual average sunset time and the distribution of day-of-test sunset time across YLS districts. Panel (a) presents annual average sunset time for all districts in YLS. Panel (b) presents daily sunset time for dates on which children were tested in math in YLS districts across survey rounds.

Table B.1: Summary Statistics: Monthly Distribution of Interview Dates in ITUS by State

	Haryana	Madhya Pradesh	Gujarat	Orissa	Tamil Nadu	Meghalaya
January	0.12	0.09	0.10	0.10	0.04	0.05
	(0.33)	(0.29)	(0.30)	(0.31)	(0.19)	(0.22)
Febuary	0.10	0.11	0.11	0.12	0.05	0.09
	(0.30)	(0.31)	(0.31)	(0.33)	(0.23)	(0.28)
March	0.05	0.10	0.07	0.05	0.15	0.12
	(0.22)	(0.30)	(0.26)	(0.22)	(0.36)	(0.33)
April	0.12	0.05	0.06	0.13	0.03	0.12
	(0.33)	(0.21)	(0.24)	(0.33)	(0.17)	(0.32)
May	0.09	0.06	0.07	0.06	0.04	0.09
	(0.28)	(0.23)	(0.26)	(0.24)	(0.21)	(0.29)
June	0.01	0.07	0.04	0.01	0.15	0.05
	(0.12)	(0.26)	(0.19)	(0.07)	(0.35)	(0.22)
July	0.08	0.07	0.03	0.11	0.01	0.06
	(0.28)	(0.26)	(0.17)	(0.31)	(0.10)	(0.24)
August	0.08	0.09	0.09	0.12	0.03	0.13
	(0.27)	(0.28)	(0.29)	(0.32)	(0.18)	(0.33)
September	0.09	0.08	0.14	0.03	0.17	0.04
	(0.29)	(0.28)	(0.35)	(0.17)	(0.37)	(0.19)
October	0.09	0.08	0.10	0.12	0.08	0.06
	(0.29)	(0.27)	(0.30)	(0.33)	(0.26)	(0.24)
November	0.12	0.07	0.08	0.11	0.07	0.20
	(0.33)	(0.26)	(0.27)	(0.32)	(0.25)	(0.40)
December	0.04	0.14	0.10	0.04	0.19	0.00
	(0.19)	(0.34)	(0.29)	(0.20)	(0.39)	(0.00)
Observations	2089	6395	4277	4057	5022	739

Notes: This table presents the monthly distribution (in proportions) of ITUS interview dates of children between 6 and 16 years of age. Standard deviations in parentheses. Source: ITUS.

Table B.2: Effect of Late Sunset on Interview Date

	(1) Survey Date (0/1) β / SE	(2) Survey Date (0/1) β / SE
Sunset Time (Hours)	-0.002	-0.004
	(0.003)	(0.005)
Mean	0.12	0.24
Observations	37960	18980
R^2	0.000	0.000

Notes: This table presents the relationship between daily sunset time and interview dates. Column 1 includes all months in years 1998 and 1999, however, because ITUS was mainly conducted between July 1998 and June 1999, Column 2 only includes July 1998 - June 1999. Homoskedastic standard errors presented in parentheses. Source: ITUS.

Table B.3: Summary Statistics: ITUS Sample Description by Type of Day

	Entire Sample (Age 6-16)	Normal Day Sample	Weekly Variant Sample
Age	11.19	11.33	10.97
	(2.95)	(2.97)	(2.89)
Years of Education	4.38	4.27	4.57
	(3.42)	(3.46)	(3.35)
Sex (0/1)	0.55	0.54	0.56
	(0.50)	(0.50)	(0.50)
Rural (0/1)	0.69	0.70	0.68
	(0.46)	(0.46)	(0.47)
Homestead (0/1)	0.65	0.65	0.64
	(0.48)	(0.48)	(0.48)
Land Owned (0/1)	0.46	0.47	0.45
	(0.50)	(0.50)	(0.50)
Land Possessed (0/1)	0.46	0.46	0.45
	(0.50)	(0.50)	(0.50)
Monthly HH Exp (INR)	2731.22	2700.74	2780.62
	(1634.11)	(1624.54)	(1648.40)
Temporary House (0/1)	0.38	0.38	0.37
	(0.48)	(0.49)	(0.48)
Semi-Temporary House (0/1)	0.23	0.23	0.22
	(0.42)	(0.42)	(0.42)
Permanent House (0/1)	0.39	0.38	0.41
	(0.49)	(0.49)	(0.49)
Primary Activity: Not a Student (0/1)	0.19	0.25	0.09
	(0.39)	(0.43)	(0.29)
Normal Days/Week	6.10	6.25	5.84
	(0.60)	(0.63)	(0.44)
Weekly Variant Days/Week	0.88	0.72	1.13
	(0.57)	(0.60)	(0.40)
Abnormal Days/Week	0.03	0.03	0.03
	(0.17)	(0.17)	(0.18)
Household Size	5.52	5.54	5.48
	(1.98)	(1.96)	(2.00)
Hinduism (0/1)	0.88	0.88	0.88
	(0.33)	(0.33)	(0.33)
Sunday (0/1)	0.28	0.04	0.66
	(0.45)	(0.19)	(0.47)
Observations	22579	13964	8615

Notes: This table presents summary statistics on both individual and household characteristics for children between 6 and 16 years of age on weekdays and weekends. Standard deviations in parentheses. Source: ITUS.

Table B.4: Summary Statistics: Non-Linear Metrics of Sleep by Age Group

	Age 6-13	Age 14-16
Sleep>7h	0.98	0.94
	(0.13)	(0.23)
Sleep>8h	0.93	0.80
	(0.25)	(0.40)
Sleep>9h	0.70	0.44
	(0.46)	(0.50)
Sleep>10h	0.34	0.13
	(0.47)	(0.33)
Sleep>11h	0.09	0.02
	(0.28)	(0.14)
Observations	9894	4070

Notes: This table presents summary statistics on the percentage of children who sleep at least 7, 8, 9, 10 or 11 hours/day on a weekday, by age group. Standard deviations in parentheses. Source: ITUS.

Table B.5: Summary Statistics: Educational Outcomes

	2015 India	2003 Indonesia
Years of Schooling	4.44	4.10
	(3.16)	(3.00)
	[638682]	[32985]
Primary (0/1)	0.48	0.34
	(0.50)	(0.47)
	[638682]	[32985]
Middle (0/1)	0.21	0.10
	(0.41)	(0.29)
	[638682]	[32985]
Age	10.99	10.79
	(3.15)	(3.18)
	[638682]	[32985]
Rural (0/1)	0.74	0.60
	(0.44)	(0.49)
	[638682]	[32985]

Notes: This table presents summary statistics on years of schooling, educational attainment, age, and rural-urban status for children between 6 and 16 years of age across India (2015) and Indonesia (2003). Standard deviations in parentheses, and number of observations in brackets. Source: DHS.

Table B.6: Summary Statistics: Educational Outcomes

	Entire Sample
Years of Schooling	4.79
	(3.10)
	[10006]
Primary (0/1)	0.52
	(0.50)
	[10006]
Middle (0/1)	0.23
	(0.42)
	[10006]
Secondary (0/1)	0.08
	(0.27)
	[10006]
Enrolled (0/1)	0.91
	(0.28)
	[9192]
Age	11.20
	(3.11)
	[10080]
Male (0/1)	0.54
	(0.50)
	[10080]

Notes: This table presents summary statistics on years of schooling, educational attainment, enrollment status, age and sex for children between 6 and 16 years of age. Standard deviations in parentheses, and number of observations in brackets. Source: REDS.

Table B.7: Summary Statistics: Village Characteristics

	Entire Sample
Number of Households	436.18
	(368.78)
No. Times In-Migration 50 yrs	7.27
	(19.16)
No. Times Out-Migration 50 yrs	2.01
	(4.44)
In-Migration for Work in 10 years (0/1)	0.71
	(0.46)
Permanent Road (0/1)	0.45
	(0.40)
Brick Houses (Prop.)	0.40
	(0.28)
Huts (Prop.)	0.08
	(0.12)
Mud Houses (Prop.)	0.27
	(0.26)
Multi-Storeyed Houses (Prop.)	0.07
	(0.12)
Public Tap (0/1)	0.45
	(0.44)
Wells (0/1)	0.34
	(0.41)
HHs Running Water (Prop.)	0.18
	(0.25)
Street Lights (0/1)	0.43
	(0.47)
HHs Electricity (Prop.)	0.42
	(0.36)
Public Toilet (0/1)	0.10
	(0.23)
HHs Indoor Toilet (Prop.)	0.23
	(0.25)
HHs Landline (Prop.)	0.09
	(0.14)
HHs Large Livestock (Prop.)	0.79
	(1.19)
HHs Bicycle (Prop.)	0.83
	(0.84)
HHs Mobile (Prop.)	0.18
	(0.30)
HHs Motorcycle (Prop.)	0.20
	(0.31)
HHs Car (Prop.)	0.02
	(0.04)
Observations	221

Notes: This table presents summary statistics on village characteristics for all REDS villages. Standard deviations in parentheses. Source: REDS.

Table B.8: Controls for Sunrise Time and Daylight Duration: Effect of Late Sunset on Sleep (Hours)

	(1) Sleep β / SE	(2) Sleep β / SE
Sunset Time (Hours)	-0.63	-0.75
	(0.55)	(1.10)
District FE	Yes	Yes
Week-of-Year FE	Yes	Yes
Sunrise Time	Yes	No
Daylight Duration	No	Yes
Mean	8.33	8.33
Observations	62768	62768
R^2	0.064	0.064

Notes: This table presents the effect of daily sunset time on time allocated to sleep by individuals over 6 years of age on weekdays in India. Column 1 controls for sunrise time and Column 2 controls for daylight duration. All regressions includes district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

ITUS Activity Classification

- Primary Production Activities
  - Crop farming, kitchen gardening, etc.
    - Ploughing, preparing land, cleaning of land
    - Sowing, planting, transplanting
    - Application of manure, fertilizer, pesticides and watering, preparing organic/manure, harvesting, threshing, picking, and winnowing
    - Weeding
    - Supervision of work.
    - Kitchen gardening - backyard cultivation
    - Stocking, transporting to home, guarding or protection of crops.

    * Sale and purchase related activities
    * Travel to the work
  - Animal husbandry
    * Grazing animals outside
    * Tending animals - cleaning, washing shed, feeding, watering, preparation of feed.
    * Caring for animals: breeding, shearing, medical treatment, grooming, shoeing etc.
    * Milking and processing of milk; collecting, storing of poultry products.
    * Making dung cakes
    * Poultry rearing - feeding, cleaning.
    * Other related activities.
    * Sale and purchase related activities
    * Travel to the work.
  - Fishing, Forestry, Horticulture, Gardening
    * Nursery - seedlings
    * Planting, tending, processing of trees.
    * Collecting, storing & stocking of fruits etc.
    * Wood cutting, chopping & stocking firewood
    * Fish farming, cleaning sea-bed, feeding fish, catching fish, gathering other aquatic life
    * Care of house plants, indoor and outdoor garden work.
    * Flower gardening -landscaping, maintenance, cutting, collecting, storing

    * Sale and purchase related activities.
    * Traveling to the work.
  - Collection of fruit, water, plants etc., storing and hunting.
    * Fetching of water
    * Collection of fruits, vegetables, berries, mushrooms etc. edible goods
    * Collection of minor forest produce, leaves, bamboo, etc.
    * Collection of fuel/fuel wood/twigs.
    * Collection of raw material for crafts.
    * Collection of building materials
    * Collection of fodder
    * Sale and purchase related activities
    * Collection of other items
    * Travel to work.
  - Processing & Storage
    * Milling, husking, pounding
    * Parboiling
    * Sorting, grading
    * Grinding, crushing
    * Any other related activity
    * Sales and purchase related activities
    * Travel for the work
  - Mining, quarrying, digging, cutting, etc.
    * Mining/extraction of salt,

  - * Mining/digging/quarrying of stone, slabs, breaking of stones for construction of building road, bridges etc.
    * Digging out clay, gravel and sand
    * Digging out minerals - major and minor
    * Transporting in vehicles
    * Storing, stocking
    * Any other related activity
    * Sale and purchase related activity
    * Travel for the work

- Secondary Activities
  - Construction Activities
    * Building & construction of dwelling (laying bricks, plastering, thatching, bamboo work, roofing) and maintenance and repairing of dwelling.
    * Construction and repair of animal shed, shelter for poultry etc.
    * Construction of wall. storage facility, fencing etc; for farms, irrigation work.
    * Construction of public works/common infrastructure - roads, buildings, bridges, etc.
    * Any other activity related.
    * Sales and purchase related activity
    * Travel to the work.
  - Manufacturing Activities
    * Food processing and cooking for sale - making pickles, spices and

other products; canning fruits, jams & jellies; baking; beverage preparation, selling readymade food etc.

    * Butchering, curing, processing, drying storing etc. of meat, fish etc.
    * Manufacturing of textiles - spinning, weaving, processing of textiles; knitting, sewing, garment making of cotton, wool and other material.
    * Making handicrafts, pottery, printing and other crafts made primarily with hands. (wood based leather based crafts, embroidery work etc.)
    * Fitting, installing, tool setting, tool and machinery - moulding, welding, tool making,
    * Assembling machines, equipment and other products,
    * Production related work in large and small factories in different industries - as production workers, maintenance workers paid trainees and apprentices, sales, administration and management activities.
    * Sale and purchase related activity
    * Travel for the work.

- Trade, Business and Services
  - Trade and Business
    * Buying and selling goods - such as capital goods, intermediate goods, consumer durables, consumer goods - in the organised and formal sectors.

    * Petty trading, street and door to door vending, hawking, shoe cleaning etc.
    * Transporting goods in trucks, tempos and motor vehicles.
    * Transporting in hand carts, animal carts, cycle rickshaws etc. or manually
    * Transport of passenger by motorized and non-motorised transports
    * Any other activity.
    * Travel to work.
- Services
    * Service in government and semi-government organisations (salaried)
    * Service in-private organisations (salaried)
    * Petty service: domestic servants, sweepers, washers, pujari, barber, cobbler, mali massaging, prostitution, watching and guarding
    * Professional services: medical and educational services (private tuition, non-formal teaching etc.), financial services and management and technical consultancy services
    * Professional services: computer services, photocopying services, beauty parlors, hair cutting saloons etc.
    * Technical services: plumbing, electrical and electronic repair and maintenance and other related services
    * Others
    * Travel to work.

- Household Maintenance, Management and Shopping for Own Household
  - (Single Sub-Category)
    * Cleaning food items, beverages and serving.
    * Cleaning and upkeep of dwelling and surroundings
    * Cleaning of utensils
    * Care of textiles: sorting, mending, washing, ironing and ordering clothes and linen
    * Shopping for goods and non-personal services: capital goods, household appliances, equipment, food and various household supplies.
    * Household management: planning, supervising, paying bills, etc.
    * Do-it-yourself home improvements and maintenance, installation, servicing and repair of personal and household goods.
    * Pet care
    * Travel related to household maintenance, management and shopping; household maintenance, management and shopping not elsewhere classified.
- Care for Children, the Sick, Elderly, and Disabled for Own Household
  - (Single Sub-Category)
    * Physical care of children: washing, dressing, feeding
    * Teaching, training and instruction of own children
    * Accompanying children to places: school, sports, lessons, etc.
    * Physical care of the sick, disabled, elderly household members: washing, dressing, feeding, helping.

    * Accompanying adults to receive personal care services: such as hairdresser's therapy sessions, temple, religious places etc.
    * Supervising children needing care - with or without other activities
    * Supervising adults needing care - with or without other activities.
    * Travel related to care of children
    * Travel related to care of adults and others.
    * Taking care of guests/visitors
    * Any other activity not mentioned above

- Community Services and Help to Other Households
  - (Single Sub-Category)
    * Community organised construction and repairs: buildings, roads, dams, wells, ponds etc. community assets.
    * Community organised work: cooking for collective celebrations, etc.
    * Volunteering with for an organisation (which does not involve working directly for individuals)
    * Volunteer work through organisations extended directly to individuals and groups
    * Participation in meetings of local and informal groups/caste, tribes, professional associations, union, fratemal and political organisations
    * Involvement in civic and related responsibilities: voting, rallies, attending meetings, panchayat
    * Informal help to other households

* Community services not elsewhere classified
* Travel related to community services

- Learning
  - (Single Sub-Category)
    * General Education: School/university/other educational institutions attendance
    * Studies, homework and course review related to general education
    * Additional study, non-formal education under adult education programmes.
    * Non formal education by children
    * Work-related training
    * Training under government programmes such as TRYSEM, DWCRA and others.
    * Other training/education
    * Learning not elsewhere classified
    * Travel related to learning
- Social and Cultural Activities, Mass Media, etc.
  - (Single Sub-Category)
    * Participating in social events: wedding, funerals, births, and other celebrations ′
    * Participating in religious activities: Church services, religious ceremonies, practices, kirtans, singing, etc.
    * Participating in community functions in music, dance etc.

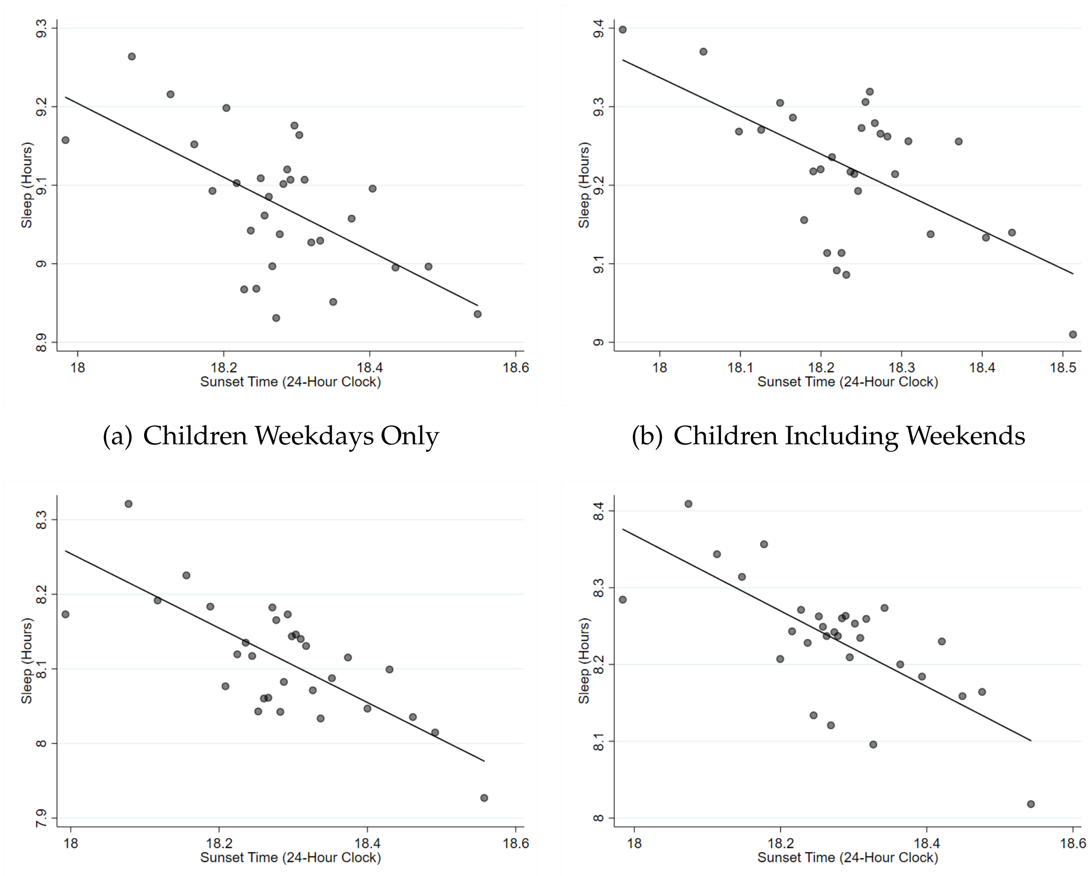
        * Socializing at home and outside the home.
        * Arts, making music, hobbies and related courses:
        * Indoor and outdoor sports participation and related courses
        * Games and other past-time activities
        * Spectator to sports, exhibitions/museums, cinema/theatre/concerts and other performances and events
        * Other related activities.
        * Reading, other than newspaper and magazines.
        * Watching television and video
        * Listening to music/radio
        * Accessing information by computing
        * Visiting library
        * Reading newspaper, magazines
        * Mass media use and entertainment not classified elsewhere
        * Travel related to social, cultural and recreational activities, social, cultural and recreational activities, social, cultural and recreational activities not elsewhere classified, mass media use and entertainment.
        * Travel relating to search of jobs.

- Personal Care and Self-Maintenance
    - (Single Sub-Category)
        * Sleep and related activities
        * Eating and drinking
        * Smoking, drinking alcohol and other intoxicants.

* Personal Hygiene and health
* Walking, exercise mining, jogging, yoga, etc.
* Receiving medical and personal care from professional
* Receiving medical and personal care from household members.
* Talking, gossiping and quarreling
* Doing nothing, rest and relaxation
* Individual religious practices and meditation
* Other activities
* Resting/convalescing due to physical illness and physically unwell persons.
* Travel related to personal care and self-maintenance

B.2 Appendix: Children's Time Use

Figure B.20: Effect of Later Sunset on Sleep



(a) Children Weekdays Only

(b) Children Including Weekends

(c) Adults Weekdays Only

(d) Adults Including Weekends

Notes: This figure presents binned scatterplots for the relationship between daily sunset time and sleep for children and adults on weekdays and weekends in India. Residuals for both sleep and sunset time are plotted after absorbing district and week-of-year fixed effects. Source: ITUS.

Table B.9: Balance Table I: Daily Sunset Time and Observables

	(1) Years of Education β / SE	(2) Worker (0/1) β / SE	(3) Sex (0/1) β / SE	(4) Rural (0/1) β / SE	(5) Household Size β / SE
Sunset Time (Hours)	0.01	0.02	-0.00	-0.00	-0.07
	(0.32)	(0.04)	(0.04)	(0.08)	(0.19)
District FE	Yes	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes	Yes
Mean	4.27	0.25	0.54	0.70	5.54
Observations	13964	13964	13964	13964	13964
R^2	0.139	0.076	0.013	0.228	0.106

Notes: This table presents the effect of daily sunset time on individual- and household-level observables for children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.10: Balance Table II: Daily Sunset Time and Observables

	(1) Hinduism (0/1) β / SE	(2) Age (Years) β / SE	(3) Homestead (0/1) β / SE	(4) Land Owned (0/1) β / SE	(5) Log Mnth HH Exp β / SE
Sunset Time (Hours)	0.04	-0.27	-0.08	-0.05	0.01
	(0.05)	(0.24)	(0.06)	(0.07)	(0.07)
District FE	Yes	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes	Yes
Mean	0.88	11.33	0.65	0.47	7.74
Observations	13964	13964	13964	13964	13964
R^2	0.255	0.023	0.448	0.159	0.217

Notes: This table presents the effect of daily sunset time on individual- and household-level observables for children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.11: Balance Table III: Daily Sunset Time and Observables

	(1) Temporary House (0/1) β / SE	(2) Semi-Temporary House (0/1) β / SE	(3) Permanent House (0/1) β / SE
Sunset Time (Hours)	-0.06	0.01	0.05
	(0.05)	(0.05)	(0.06)
District FE	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes
Mean	0.38	0.23	0.38
Observations	13964	13964	13964
R^2	0.325	0.115	0.286

Notes: This table presents the effect of daily sunset time on individual- and household-level observables for children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.12: Tobit: Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE
Sunset Time (Hours)	-0.47***	-1.31***	1.65***	-0.15
	(0.14)	(0.42)	(0.41)	(0.69)
District FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	9.07	1.50	7.60	2.05
Observations	13964	13964	13964	13964

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure and work by children between 6 and 16 years of age on weekdays. Each column represents a separate tobit regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.13: Effect of Late Sunset on Children's Study Effort (0/1)

	(1) Study (0/1) β / SE	(2) Study (0/1) β / SE
Sunset Time (Hours)	-0.10	-0.14**
	(0.06)	(0.06)
Sunset Time*Worker		0.19***
		(0.02)
District FE	Yes	Yes
Week-of-Year FE	Yes	Yes
Mean	0.57	0.57
Observations	13964	13964
R^2	0.177	0.497

Notes: This table presents the effect of daily sunset time on study effort (0/1) for children 6 and 16 years of age on weekdays in India. Each column represents a separate regression estimating Equation (8) on the outcome variable. Column 2 also includes an interaction term that captures the effect of an hour delay in daily sunset time for child laborers compared to students. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.14: Weather Controls: Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE
Sunset Time (Hours)	-0.48***	-0.70***	1.99***	0.12
	(0.17)	(0.26)	(0.44)	(0.38)
District FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Mean	9.07	1.50	7.60	2.05
Observations	13964	13964	13964	13964
R^2	0.091	0.169	0.295	0.071

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure and work by children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects, and controls for rainfall and temperature. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.15: Controlling for Observables: Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE
Sunset Time (Hours)	-0.48***	-0.64***	1.54***	0.05
	(0.13)	(0.23)	(0.40)	(0.26)
Years of Education	-0.03***	0.06***	0.05***	-0.17***
	(0.00)	(0.01)	(0.01)	(0.01)
Primary Activity: Not a Student (0/1)	0.23***	-1.56***	1.51***	3.83***
	(0.04)	(0.06)	(0.12)	(0.11)
Sex (0/1)	0.09***	0.04*	0.37***	-0.57***
	(0.02)	(0.03)	(0.05)	(0.04)
Rural (0/1)	0.22***	-0.32***	-0.33***	0.42***
	(0.05)	(0.07)	(0.11)	(0.07)
Homestead (0/1)	0.00	0.04	0.23**	-0.25***
	(0.04)	(0.06)	(0.10)	(0.08)
Land Owned (0/1)	-0.03	0.08	-0.12	-0.01
	(0.07)	(0.09)	(0.17)	(0.12)
Land Possessed (0/1)	0.04	-0.05	-0.13	0.12
	(0.07)	(0.09)	(0.16)	(0.12)
Log Mnth HH Exp	-0.14***	0.12***	-0.03	-0.15**
	(0.04)	(0.05)	(0.08)	(0.06)
Semi-Temporary House (0/1)	-0.04	0.11**	-0.02	0.01
	(0.04)	(0.05)	(0.09)	(0.07)
Permanent House (0/1)	-0.11**	0.12**	0.16*	-0.04
	(0.04)	(0.06)	(0.10)	(0.08)
Household Size	0.03***	-0.02	0.03*	-0.02*
	(0.01)	(0.01)	(0.02)	(0.01)
Hinduism (0/1)	-0.13**	0.11	-0.09	0.05
	(0.05)	(0.08)	(0.13)	(0.09)
District FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Age-by-DayofWeek FE	Yes	Yes	Yes	Yes
Mean	9.07	1.50	7.60	2.05
Observations	13964	13964	13964	13964
R^2	0.247	0.365	0.348	0.554

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure and work by children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district, week-of-year and age-by-day-of-week fixed effects, and controls for education, sex, rural-urban status, wealth, income, household size and religion. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.16: Effect of Late Sunset on Children's Time Use on Weekends (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE
Sunset Time (Hours)	-0.57***	-0.27	1.00**	-0.33
	(0.20)	(0.29)	(0.44)	(0.38)
District FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	9.46	1.73	11.28	1.36
Observations	8615	8615	8615	8615
R^2	0.123	0.284	0.116	0.126

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure and work by children between 6 and 16 years of age on weekends. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.17: State-by-Season FE: Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE
Sunset Time (Hours)	-0.53*	-0.53	0.82	-0.06
	(0.27)	(0.49)	(0.60)	(0.60)
District FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
State-by-Season FE	Yes	Yes	Yes	Yes
Mean	9.07	1.50	7.60	2.05
Observations	13964	13964	13964	13964
R^2	0.095	0.181	0.313	0.076

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure and work by children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district, week-of-year and state-by-season fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.18: Latitude-by-Week-of-Year FE: Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE
Sunset Time (Hours)	-0.64***	-0.69**	1.92***	0.19
	(0.20)	(0.29)	(0.55)	(0.50)
District FE	Yes	Yes	Yes	Yes
Latitude-by-Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	9.07	1.50	7.60	2.05
Observations	13964	13964	13964	13964
R^2	0.101	0.179	0.309	0.078

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure and work by children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district, week-of-year and latitude-by-week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.19: District-by-Season FE: Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE
Sunset Time (Hours)	-0.62**	-0.76	1.09*	-0.13
	(0.29)	(0.50)	(0.60)	(0.63)
District-by-Season FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	9.07	1.50	7.60	2.05
Observations	13964	13964	13964	13964
R^2	0.140	0.221	0.347	0.106

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure and work by children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district, week-of-year and district-by-season fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.20: Remove Summer (Vacations): Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE
Sunset Time (Hours)	-0.33*	-1.03***	0.70*	-1.40***
	(0.19)	(0.36)	(0.39)	(0.47)
District FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	9.09	1.70	6.85	1.95
Observations	10620	10620	10620	10620
R^2	0.101	0.130	0.103	0.080

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure and work by children between 6 and 16 years of age on weekdays after removing the months of April, May, and June from the sample. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.21: Remove Winter: Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE
Sunset Time (Hours)	-0.36	-0.42	1.99***	0.70
	(0.22)	(0.32)	(0.60)	(0.50)
District FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	9.05	1.37	8.04	2.17
Observations	8951	8951	8951	8951
R^2	0.091	0.205	0.332	0.077

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure and work by children between 6 and 16 years of age on weekdays after removing the months of December, January, February, and March from the sample. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.22: Remove Monsoon: Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE
Sunset Time (Hours)	-0.50***	-0.50**	1.79***	0.46
	(0.15)	(0.24)	(0.47)	(0.34)
District FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	9.09	1.47	7.81	2.02
Observations	10700	10700	10700	10700
R^2	0.092	0.189	0.332	0.068

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure and work by children between 6 and 16 years of age on weekdays after removing the months of July, August, and September from the sample. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.23: Remove Autumn: Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE
Sunset Time (Hours)	-0.57***	-0.73***	1.76***	0.27
	(0.15)	(0.27)	(0.43)	(0.35)
District FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	9.06	1.45	7.78	2.09
Observations	11621	11621	11621	11621
R^2	0.100	0.171	0.310	0.073

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure and work by children between 6 and 16 years of age on weekdays after removing the months of October and November from the sample. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.24: District-Age-Season FE: Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE
Sunset Time (Hours)	-0.53*	-0.71	1.04*	-0.35
	(0.29)	(0.53)	(0.61)	(0.62)
District-Age-Season FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	9.07	1.50	7.60	2.05
Observations	13964	13964	13964	13964
R^2	0.368	0.328	0.465	0.379

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure and work by children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district-by-age-by-season and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.25: District-Day-of-Week-Season FE: Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE
Sunset Time (Hours)	-0.61*	-0.90	1.54**	-0.42
	(0.32)	(0.55)	(0.71)	(0.68)
District-DayofWeek-Season FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	9.07	1.50	7.60	2.05
Observations	13964	13964	13964	13964
R^2	0.251	0.333	0.426	0.220

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure and work by children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district-by-day-of-week-by-season and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.26: District-Sex-Season FE: Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE
Sunset Time (Hours)	-0.63**	-0.76	1.21**	-0.17
	(0.29)	(0.50)	(0.60)	(0.62)
District-Sex-Season FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	9.07	1.50	7.60	2.05
Observations	13964	13964	13964	13964
R^2	0.155	0.238	0.368	0.144

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure and work by children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district-by-sex-by-season and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.27: District-Rural-Season FE: Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE
Sunset Time (Hours)	-0.62**	-0.78	0.89	-0.29
	(0.30)	(0.52)	(0.59)	(0.64)
District-Rural-Season FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	9.07	1.50	7.60	2.05
Observations	13964	13964	13964	13964
R^2	0.196	0.285	0.387	0.142

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure and work by children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district-by-rural-by-season and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.28: District-Wealth-Season FE: Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE
Sunset Time (Hours)	-0.51*	-0.66	0.68	0.06
	(0.28)	(0.49)	(0.58)	(0.62)
District-Rich-Season FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	9.07	1.50	7.60	2.05
Observations	13964	13964	13964	13964
R^2	0.175	0.265	0.373	0.138

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure and work by children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district-by-wealth-by-season and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.29: Conley Standard Errors: Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE
Sunset Time (Hours)	-0.47***	-0.67**	1.65***	0.10
	(0.13)	(0.26)	(0.53)	(0.35)
Observations	13964	13964	13964	13964
R^2	0.002	0.002	0.005	0.000

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure and work by children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects. Standard errors are adjusted to reflect spatial dependence as modeled in (103). Spatial autocorrelation is assumed to linearly decrease in distance up to a cutoff of 500 km. Source: ITUS.

Table B.30: Standard Errors Clustered at the District Level: Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE
Sunset Time (Hours)	-0.47***	-0.67**	1.65**	0.10
	(0.17)	(0.33)	(0.65)	(0.35)
District FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	9.07	1.50	7.60	2.05
Observations	13964	13964	13964	13964
R^2	0.091	0.169	0.294	0.070

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure and work by children between 6 and 16 years of age on weekdays in India. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district level. Source: ITUS.

Table B.31: Dropping 'Nappers': Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE
Sunset Time (Hours)	-0.39***	-0.97***	2.08***	0.23
	(0.14)	(0.28)	(0.39)	(0.40)
District FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	9.07	1.66	6.93	2.04
Observations	11350	11350	11350	11350
R^2	0.098	0.190	0.234	0.099

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure and work by children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects. I only include children who did not take naps. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Non-Linear Metrics of Sleep Duration

Unfortunately, medical experts do not agree on how much sleep children need (see (264) and (296) for a systematic review). The National Sleep Foundation (NSF) recommends 8.5 to 9.25 hours of sleep. While the National Heart, Lung and Blood Institute (NHLBI) and the Harvard Medical School recommend 10 hours and 9 hours of sleep for children between 5-18 years of age, respectively. Recently, a NSF assembled multidisciplinary expert panel recommended that children between 6 and 13 years of age sleep 9 to 11 hours while those between 14 and 17 years of age were recommended to sleep 8 to 10 hours (199). The American Academy of Sleep Medicine issued a similar recommendation (309).

In light of these recommendations, I estimate the effects of later sunset on non-linear metrics of sleep duration for children by two age-groups: 6-13 and 14-17 year olds (Table B.32). I find that an hour delay in sunset decreases the likelihood of getting 8 hours of sleep by 1 and 4 percentage points for children who are 6-13 and 14-16 year old, respectively. Although these point estimates are not statistically significant. However, I show an hour delay in sunset decreases the likelihood of getting 9 hours of sleep by roughly 15 percentage points for both age-groups.

Table B.32: Effect of Late Sunset on Sleep for School-Age Children

	(1) Age 6-13 Sleep>8h (0/1) β / SE	(2) Age 14-16 Sleep>8h (0/1) β / SE	(3) Age 6-13 Sleep>9h (0/1) β / SE	(4) Age 14-16 Sleep>9h (0/1) β / SE
Sunset Time (Hours)	-0.01	-0.04	-0.14**	-0.17**
	(0.03)	(0.05)	(0.06)	(0.08)
District FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	0.93	0.80	0.70	0.44
Observations	9894	4070	9894	4070
R^2	0.043	0.086	0.120	0.121

Notes: This table presents the effect of daily sunset time on non-linear metrics of sleep duration for children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.33: China: Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Leisure-SS β / SE	(3) Leisure-MF β / SE	(4) Homework-MF β / SE	(5) Homework-SS β / SE
Annual Average Sunset Time (Hours)	-0.43**	0.37	0.81	-0.27	-0.44
	(0.21)	(0.68)	(0.56)	(0.27)	(0.29)
Province FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Mean	9.03	3.95	2.41	1.09	1.41
Observations	5794	5794	5794	5794	5794
R^2	0.029	0.046	0.015	0.050	0.058

Notes: This table presents the effect of annual average sunset time on time allocated to sleep, leisure and homework by children between 6 and 16 years of age. Each column represents a separate regression estimating Equation (9) on the outcome variable. 'MF' denotes Monday-Friday and 'SS' denotes Saturday and Sunday. All regressions include province and year fixed effects. Standard errors are in parentheses, clustered at the county-year level. Source: CHNS.

Table B.34: Controlling for Observables: Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Leisure-SS β / SE	(3) Leisure-MF β / SE	(4) Homework-MF β / SE	(5) Homework-SS β / SE
Annual Average Sunset Time (Hours)	-0.44**	0.19	0.97*	-0.21	-0.39
	(0.21)	(0.73)	(0.54)	(0.23)	(0.29)
Age	-0.15***	0.04**	-0.03**	0.08***	0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Rural	0.16***	-0.40**	-0.22**	-0.10*	-0.00
	(0.05)	(0.16)	(0.09)	(0.05)	(0.06)
Log HH Income	-0.00	0.05	0.03*	0.01	0.02
	(0.01)	(0.03)	(0.02)	(0.01)	(0.02)
Log HH Expense	0.01	0.00	0.00	-0.00	-0.00
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
HH Size	-0.01	-0.08***	0.02	-0.02	-0.04***
	(0.01)	(0.03)	(0.03)	(0.01)	(0.01)
Energy(kcal)	-0.00	-0.01	-0.01	-0.01**	-0.01*
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)
Carbohydrates(g)	0.00	0.03	0.03	0.03**	0.02*
	(0.01)	(0.04)	(0.02)	(0.01)	(0.01)
Fat(g)	0.01	0.08	0.07	0.06**	0.06*
	(0.02)	(0.10)	(0.05)	(0.03)	(0.03)
Protein(g)	0.00	0.04	0.03	0.03**	0.02*
	(0.01)	(0.04)	(0.02)	(0.01)	(0.01)
Urbanization Index	-0.01	0.06*	0.03	0.00	-0.01
	(0.01)	(0.03)	(0.02)	(0.01)	(0.01)
Communications Component Score	0.02	-0.01	-0.07	-0.02	-0.01
	(0.02)	(0.06)	(0.05)	(0.03)	(0.03)
Community Population Density Category	0.03	-0.05	-0.03	0.00	0.02
	(0.02)	(0.05)	(0.05)	(0.02)	(0.03)
Diversity Score	0.02	0.05	0.02	0.00	0.01
	(0.02)	(0.06)	(0.04)	(0.03)	(0.04)
Economic Component Score	0.02	-0.06	-0.02	0.01	0.03
	(0.02)	(0.04)	(0.03)	(0.02)	(0.02)
Quality of Health Score	0.00	-0.06	-0.03	-0.00	0.02
	(0.01)	(0.04)	(0.03)	(0.02)	(0.02)
Housing Component Score	0.02	-0.13*	-0.02	0.02	0.04
	(0.03)	(0.07)	(0.06)	(0.03)	(0.03)
Market Component Score	0.02	-0.06	-0.02	-0.00	-0.00
	(0.01)	(0.04)	(0.03)	(0.01)	(0.02)
Social Services Score	0.01	-0.08**	-0.03	-0.00	0.01
	(0.01)	(0.04)	(0.03)	(0.01)	(0.02)
Transportation Component Score	-0.00	-0.09**	-0.04	0.01	0.01
	(0.01)	(0.04)	(0.03)	(0.02)	(0.02)
Community Education Category	0.00	-0.08	-0.12***	0.02	0.07**
	(0.02)	(0.07)	(0.04)	(0.02)	(0.03)
Modern Markets Component Score	0.00	-0.05	-0.03	-0.00	0.00
	(0.01)	(0.04)	(0.03)	(0.02)	(0.02)
Province FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes
Mean	9.04	3.96	2.43	1.10	1.41
Observations	5471	5471	5471	5471	5471
R^2	0.231	0.079	0.025	0.105	0.136

Notes: This table presents the effect of annual average sunset time on time allocated to sleep, leisure and homework by children between 6 and 16 years of age. 'MF' denotes Monday-Friday and SS denotes Saturday and Sunday. Each column represents a separate regression estimating Equation (9) on the outcome variable. All regressions include province and year fixed effects, and controls for weather, age, rural-urban status, income, household size, food consumption, and village infrastructure. Standard errors are in parentheses, clustered at the county-year level. Source: CHNS.

Table B.35: China: Effect of Late Sunset on Outdoor vs. Indoor Leisure (Hours)

	(1) Outdoor Leisure-SS β / SE	(2) Outdoor Leisure-MF β / SE	(3) Indoor Leisure-SS β / SE	(4) Indoor Leisure-MF β / SE
Annual Average Sunset Time (Hours)	0.21	0.19	0.16	0.62
	(0.17)	(0.19)	(0.59)	(0.45)
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Mean	0.34	0.30	3.61	2.11
Observations	5794	5794	5794	5794
R^2	0.015	0.017	0.046	0.015

Notes: This table presents the effect of annual average sunset time on time allocated to indoor and outdoor leisure by children between 6 and 16 years of age. 'MF' denotes Monday-Friday and SS denotes Saturday and Sunday. Each column represents a separate regression estimating Equation (9) on the outcome variable. All regressions include province and year fixed effects. Standard errors are in parentheses, clustered at the county-year level. Source: CHNS.

Outdoor Leisure and Later Sunset Times

If outdoor activities enjoy increasing returns to scale during daylight, later sunset may induce children to engage in longer outdoor recreational activities in the evening, which would be less satisfying if performed separately over the same duration but broken between morning and evening. For instance, (421) find that reallocation of available daylight from the morning to the evening and back due to daylight saving time causes a reallocation of time from indoor to outdoor recreational activities and back again.

To test this hypothesis, I disaggregate time allocated to leisure by outdoor and indoor activities.[6] First, I show that the increase in leisure is largely driven by indoor and not outdoor recreation (Table B.36), consistent with studies that show that sleep deprivation increases daytime sleepiness and sedentary leisure activities. Second, I examine the effects of later sunset on children's time use by hour of day. Although there is some evidence for substitution between indoor leisure and outdoor leisure in the evening (6 pm), children do not directly

[6] I define outdoor leisure as any recreational activity performed outside the house, or any indoor activity for which one has to initially leave the house and go to another indoor or outdoor location (e.g., relatives' house).

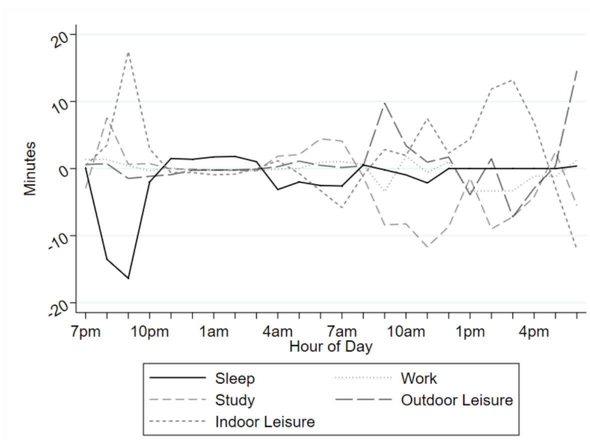
substitute sleep with outdoor leisure (Figure B.21).

Table B.36: Effect of Late Sunset on Children's Outdoor vs. Indoor Leisure

	(1) Leisure - Indoor β / SE	(2) Leisure - Indoor β / SE	(3) Leisure - Outdoor β / SE	(4) Leisure - Outdoor β / SE
Sunset Time (Hours)	1.18***	0.79	0.47**	0.30
	(0.32)	(0.55)	(0.21)	(0.32)
District FE	Yes	No	Yes	No
Week-of-Year FE	Yes	Yes	Yes	Yes
District-by-Season FE	No	Yes	No	Yes
Mean	5.74	5.74	1.86	1.86
Observations	13964	13964	13964	13964
R^2	0.223	0.268	0.174	0.233

Notes: This table presents the effect of daily sunset time on time allocated to indoor and outdoor leisure by children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable; columns 1 and 3 includes district and week-of-year fixed effects, while columns 2 and 4 include district-by-season and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Figure B.21: Effect of Late Sunset on Children's Time Use by Hour of Day



Notes: This figure presents the effect of daily sunset time on time allocated to sleep, study, leisure and work by children between 6 and 16 years of age on weekdays. Each line on the graph represents 24 separate regressions estimating Equation (8) on the outcome variable – one for each hour in the day. All regressions in the left figure include district-by-season and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Effect of Later Sunset on Specific Leisure Activities

In this section, I examine the effects of later sunset on indoor and outdoor leisure, disaggregated by type of leisure activity. I present estimates generated after absorbing both district fixed effects and district-by-season fixed effects because the effect of later sunset on the *type of leisure activity* is sensitive to district-specific seasonal confounders.

Indoor Leisure: Tables B.37 and B.38 present impacts on specific indoor leisure activities. I find that the effect on indoor leisure is largely driven by 'Doing Nothing', 'Nap', and 'Talking, Gossiping'. The category 'Doing Nothing' includes time spent doing nothing, resting and relaxing. The category 'Talking, Gossiping' includes time allocated to talking, gossiping or quarreling. I find no change in time allocated to mass media or eating and hygiene. Since afternoon naps are responsible for a significant proportion of the increase in indoor leisure, these results are precisely what one would expect if children's need for sleep and likely sleep deprivation increases compensatory (sedentary) leisure activities as documented by several medical studies (87; 88; 153; 217; 301; 338).

Daytime Naps: What does the point estimate on daytime naps mean for the effect of later sunset on children's *total* sleep ('Sleep and Nap')? Table B.37 shows that an hour delay in sunset increases daytime sleep by over 15 minutes. Thus, the negative effect on *total* sleep is roughly 15 minutes (Tables B.39 and B.40), although the point estimate is underpowered.[7] In addition, Tables B.41

[7] I also find virtually identical estimates for adults (Table B.76). Furthermore, the coefficient on 'Sleep and Nap' is statistically significant, presumably because the adults' sample includes almost four times as many observations as the children's sample.

and B.42 examine the effects of later sunset on non-linear metrics of *total* sleep duration and finds that among 6-13 year olds an hour delay in sunset reduces the likelihood of getting 9 hours of *total* sleep by 11 percentage points. This effect size is identical to that observed in Table B.32 for non-linear metrics of *nighttime* sleep duration.

This discussion should not distract from the fact that naps may not provide the same biochemical therapeutic effects on the brain as longer periods of nocturnal sleep, and do not make up for inadequate nighttime sleep (The National Sleep Foundation).[8][9] Naps may momentarily increase basic concentration under conditions of sleep deprivation, as caffeine can up to a certain dose. But, naps cannot salvage more complex functions of the brain, including learning, memory, emotional stability, complex reasoning, or decision-making (417). In addition, daytime naps take place after school hours. Thus, any short-term benefits of napping on cognition will not mitigate the negative effect of (nighttime) sleep deprivation on learning in school. That is, while post-learning sleep (naps) may help consolidate memories, pre-learning sleep (nighttime sleep) is crucial for the encoding of new memories (22; 410; 416; 424). In fact, the effect of pre-learning sleep is precisely what is observed by studies investigating the impact of later school start times on test scores (86; 147; 195; 414)

Outdoor Leisure: Tables B.43 and B.44 presents impacts on specific outdoor leisure activities. I find that the effect on outdoor leisure is driven by 'Games, Pastime'. An hour delay in sunset time increases time spent on games and other

[8]See https://www.sleepfoundation.org/sleep-topics/napping.

[9]In fact, studies conducted among preschool-aged children show that daytime naps are negative correlated with performance on cognitive tasks, while nighttime sleep is positive correlated. One interpretation of these results is that children who receive inadequate sleep at night are more likely to take daytime naps (239; 240), which is consistent with my findings.

pastime by roughly 20 minutes. It is important to note that although coded as outdoor leisure, 'Games, Pastime' may include indoor activities like board games. I fail to find a significant effect of later sunset on travel for leisure or running and exercise.

Table B.37: Effect of Late Sunset on Children's Indoor Leisure Activities (Hours)

	(1) Nap β / SE	(2) Mass Media β / SE	(3) Eating, Hygiene β / SE	(4) Doing Nothing β / SE	(5) Talking, Gossiping β / SE	(6) Other Indoor β / SE
Sunset Time (Hours)	0.27**	0.03	-0.12	0.79***	0.19*	0.03
	(0.11)	(0.22)	(0.10)	(0.14)	(0.10)	(0.07)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean	0.36	1.06	2.40	1.03	0.69	0.19
Observations	13964	13964	13964	13964	13964	13964
R^2	0.246	0.157	0.237	0.185	0.176	0.057

Notes: This table presents the effect of daily sunset time on time allocated to indoor leisure activities by children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.38: District-by-Season FE: Effect of Late Sunset on Children's Indoor Leisure Activities (Hours)

	(1) Nap β / SE	(2) Mass Media β / SE	(3) Eating, Hygiene β / SE	(4) Doing Nothing β / SE	(5) Talking, Gossiping β / SE	(6) Other Indoor β / SE
Sunset Time (Hours)	0.34**	0.14	-0.09	0.02	0.37*	0.02
	(0.15)	(0.38)	(0.20)	(0.27)	(0.22)	(0.16)
District-by-Season FE	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean	0.36	1.06	2.40	1.03	0.69	0.19
Observations	13964	13964	13964	13964	13964	13964
R^2	0.336	0.214	0.283	0.260	0.226	0.100

Notes: This table presents the effect of daily sunset time on time allocated to indoor leisure activities by children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district-by-season and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.39: Effect of Late Sunset on Sleep and Nap for School-Age Children

	(1) Sleep β / SE	(2) Nap β / SE	(3) Sleep and Nap β / SE
Sunset Time (Hours)	-0.47***	0.27**	-0.20
	(0.14)	(0.11)	(0.20)
District FE	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes
Mean	9.07	0.36	9.44
Observations	13964	13964	13964
R^2	0.091	0.246	0.099

Notes: This table presents the effect of daily sunset time on sleep for children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.40: District-by-Season FE: Effect of Late Sunset on Sleep and Nap for School-Age Children

	(1) Sleep β / SE	(2) Nap β / SE	(3) Sleep and Nap β / SE
Sunset Time (Hours)	-0.62**	0.34**	-0.28
	(0.29)	(0.15)	(0.33)
District-by-Season FE	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes
Mean	9.07	0.36	9.44
Observations	13964	13964	13964
R^2	0.140	0.336	0.168

Notes: This table presents the effect of daily sunset time on sleep for children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district-by-season and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.41: Non-Linear Metrics of Sleep: Effect of Late Sunset on Sleep and Nap for School-Age Children

	(1) Age 6-13 Sleep and Nap>8h β / SE	(2) Age 14-16 Sleep and Nap>8h β / SE	(3) Age 6-13 Sleep and Nap>9h β / SE	(4) Age 14-16 Sleep and Nap>9h β / SE
Sunset Time (Hours)	0.01	-0.02	-0.11**	-0.04
	(0.02)	(0.05)	(0.05)	(0.08)
District FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	0.95	0.83	0.76	0.52
Observations	9894	4070	9894	4070
R^2	0.043	0.081	0.081	0.095

Notes: This table presents the effect of daily sunset time on sleep for children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.42: District-by-Season FE: Non-Linear Metrics of Sleep: Effect of Late Sunset on Sleep and Nap for School-Age Children

	(1) Age 6-13 Sleep and Nap>8h β / SE	(2) Age 14-16 Sleep and Nap>8h β / SE	(3) Age 6-13 Sleep and Nap>9h β / SE	(4) Age 14-16 Sleep and Nap>9h β / SE
Sunset Time (Hours)	0.00	-0.28**	-0.14	-0.22
	(0.05)	(0.12)	(0.10)	(0.16)
District-by-Season FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	0.95	0.83	0.76	0.52
Observations	9894	4070	9894	4070
R^2	0.084	0.143	0.146	0.177

Notes: This table presents the effect of daily sunset time on sleep for children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district-by-season and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.43: Effect of Late Sunset on Children's Outdoor Leisure Activities (Hours)

	(1) Running, Exercise β / SE	(2) Travel for Leisure β / SE	(3) Games, Pastime β / SE	(4) Other Outdoor β / SE
Sunset Time (Hours)	0.10	0.04	0.32	0.01
	(0.07)	(0.04)	(0.20)	(0.05)
District FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	0.21	0.12	1.46	0.08
Observations	13964	13964	13964	13964
R^2	0.100	0.175	0.154	0.063

Notes: This table presents the effect of daily sunset time on time allocated to outdoor leisure activities by children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

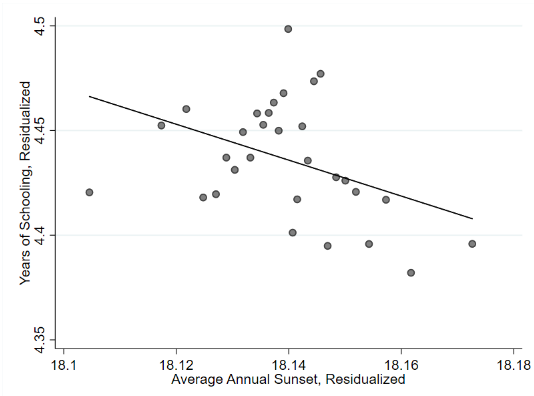
Table B.44: District-by-Season FE: Effect of Late Sunset on Children's Outdoor Leisure Activities (Hours)

	(1) Running, Exercise β / SE	(2) Travel for Leisure β / SE	(3) Games, Pastime β / SE	(4) Other Outdoor β / SE
Sunset Time (Hours)	0.14	-0.04	0.51	-0.31***
	(0.13)	(0.07)	(0.31)	(0.08)
District-by-Season FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	0.21	0.12	1.46	0.08
Observations	13964	13964	13964	13964
R^2	0.157	0.297	0.219	0.128

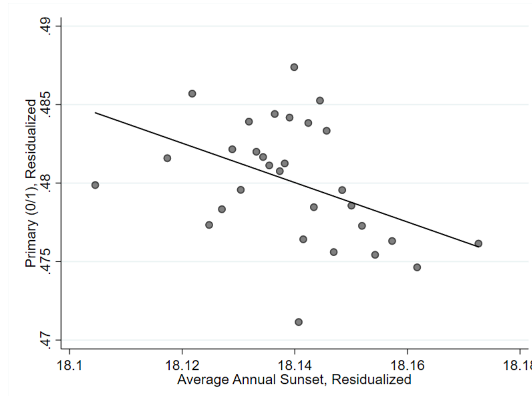
Notes: This table presents the effect of daily sunset time on time allocated to outdoor leisure activities by children between 6 and 16 years of age on weekdays. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district-by-season and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

B.3 Appendix: Children's Academic Outcomes

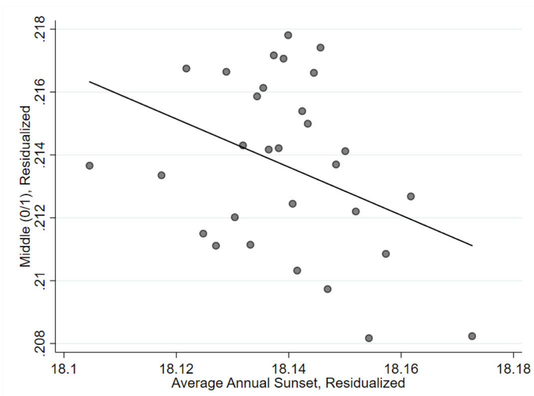
Figure B.22: Effect of Late Sunset on Years of Schooling, Educational Attainment, and Enrollment Status



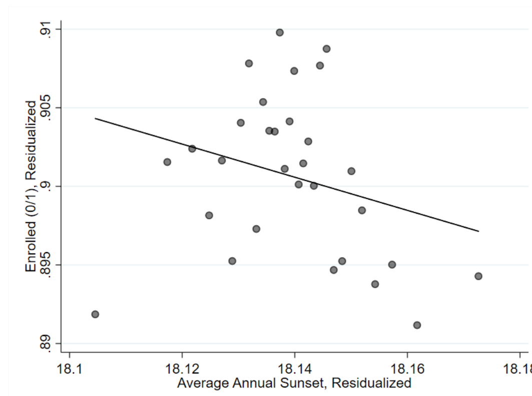
(a) Years of Schooling



(b) Primary School (0/1)



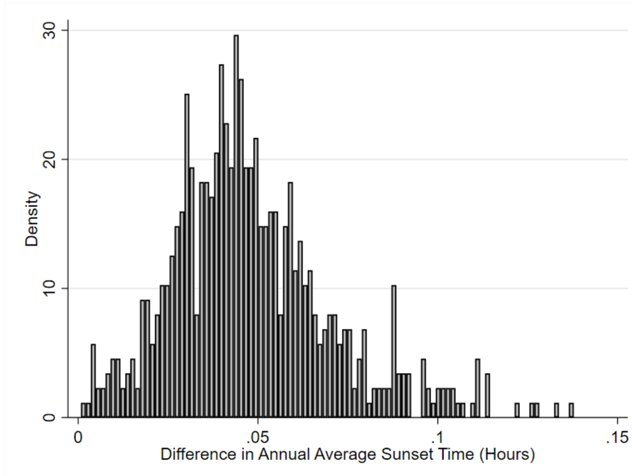
(c) Middle School (0/1)



(d) Enrolled (0/1)

Notes: This figure presents binned scatterplots for the relationship between academic outcomes and annual average sunset time (24-hour clock) for children between 6 and 16 years of age in India. Residuals for both academic outcomes and annual average sunset are plotted after absorbing district and age fixed effects. Source: DHS.

Figure B.23: Within-District Variation in Annual Average Sunset Time



Notes: This figure presents within-district variation in annual average sunset time or the distribution of difference in annual average sunset time between the easternmost and westernmost PSUs within a district. Source: DHS.

Figure B.24: DHS Clusters in Indonesia and Time Zone Boundary on the Kalimantan Island

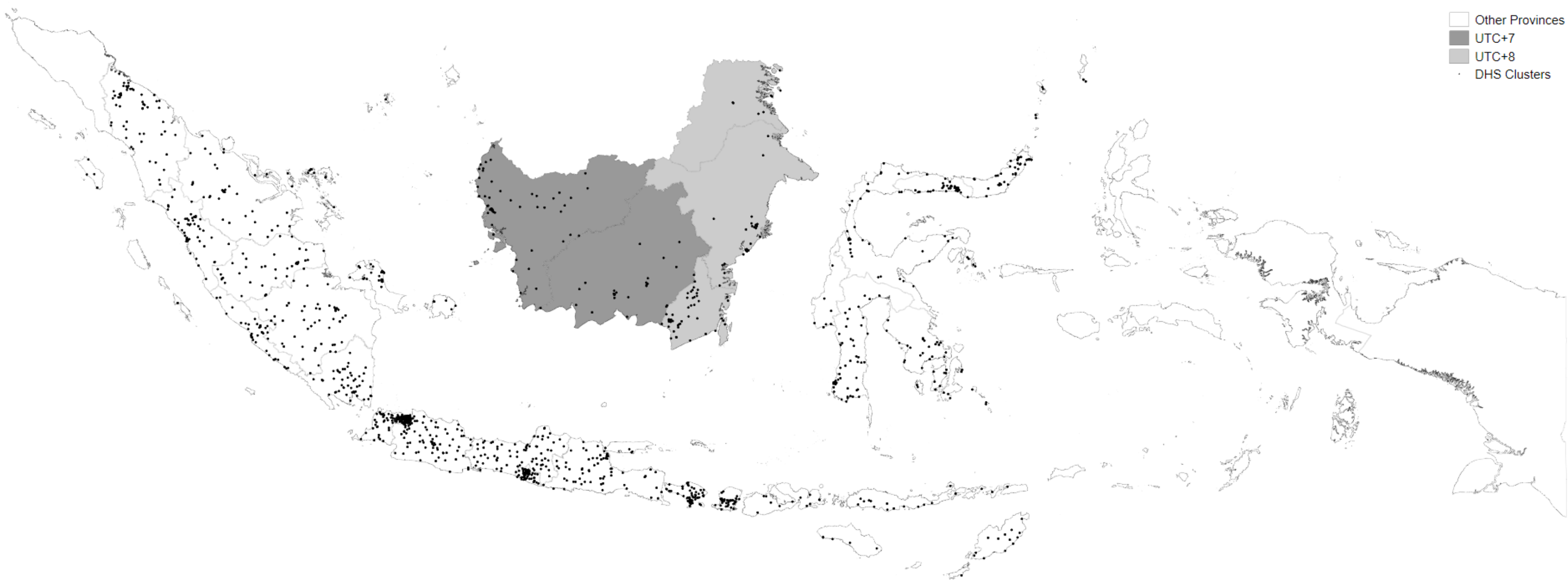
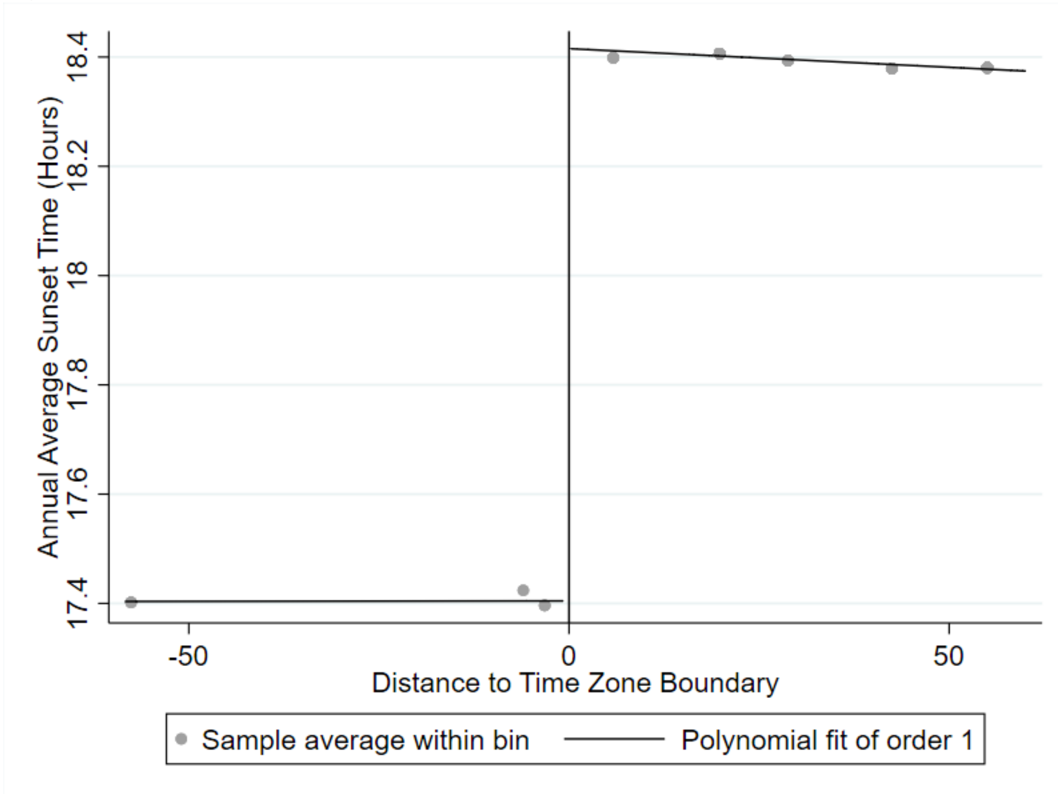
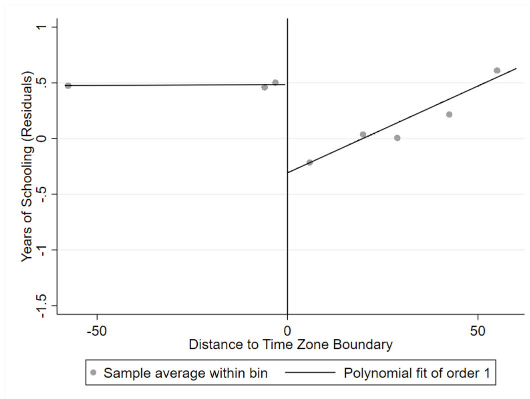


Figure B.25: Indonesia Regression Discontinuity Estimates: Discontinuity in Average Annual Sunset Time at Time Zone Border

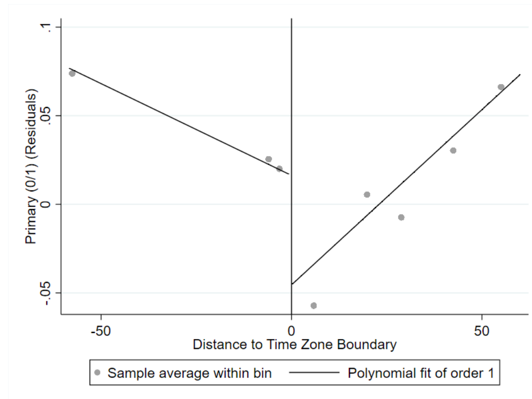


Notes: This figure presents the sharp one-hour discontinuity in annual average sunset time for DHS PSUs on either side of the time zone border (as depicted in Figure B.24) on Kalimantan, Indonesia. Source: DHS.

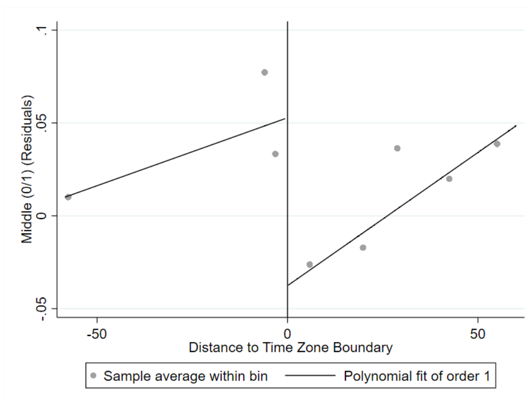
Figure B.26: Indonesia Regression Discontinuity Estimates: Effects of Later Sunset on Years of Schooling, Educational Attainment, and Enrollment (Polynomial Fit of Order 1)



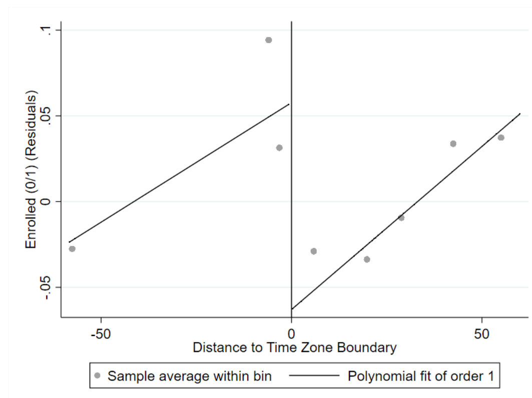
(a) Years of Schooling



(b) Primary School (0/1)



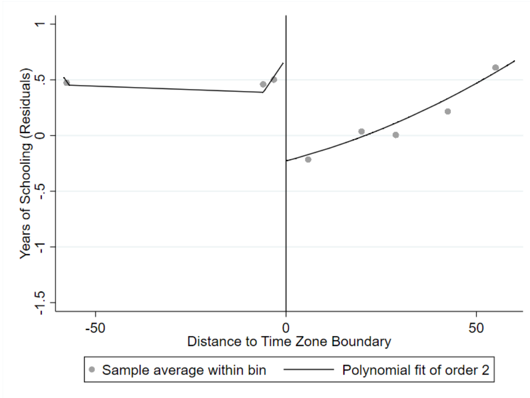
(c) Middle School (0/1)



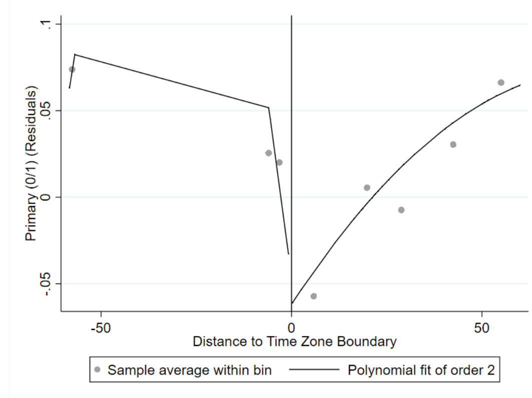
(d) Enrollment Status (0/1)

Notes: This figure presents the effects of annual average sunset time on years of schooling, educational attainment and enrollment for children between 6 and 16 years of age in Indonesia. I leverage discontinuity in annual average sunset time (Figure B.25) for DHS PSUs on either side of the time zone border (as depicted in Figure B.24) on Kalimantan, Indonesia. All regressions include controls for age. Source: DHS.

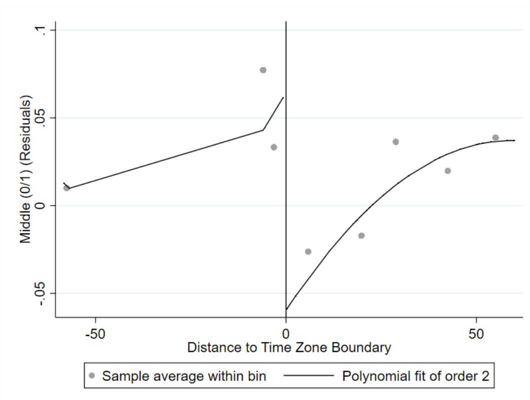
Figure B.27: Indonesia Regression Discontinuity Estimates: Effects of Later Sunset on Years of Schooling, Educational Attainment, and Enrollment (Polynomial Fit of Order 2)



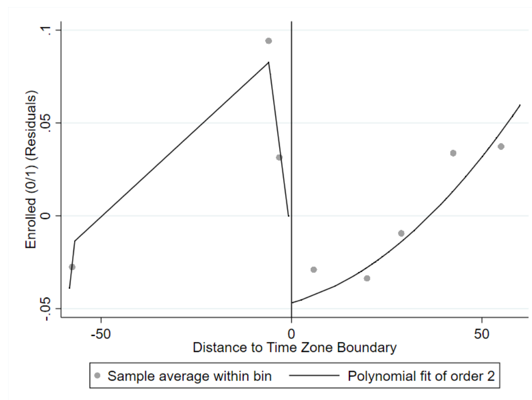
(a) Years of Schooling



(b) Primary School (0/1)



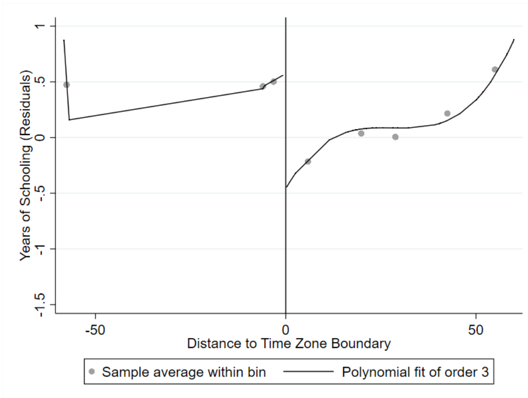
(c) Middle School (0/1)



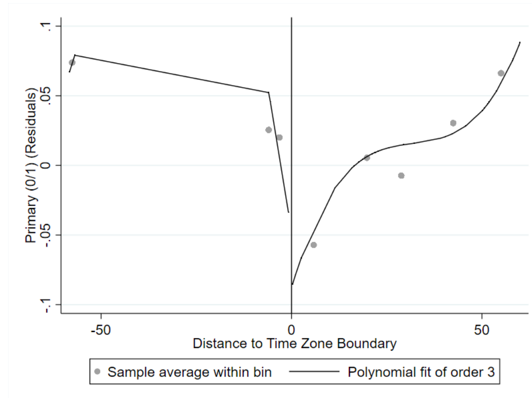
(d) Enrollment Status (0/1)

Notes: This figure presents the effects of annual average sunset time on years of schooling, educational attainment and enrollment for children between 6 and 16 years of age. I leverage discontinuity in annual average sunset time (Figure B.25) for DHS PSUs on either side of the time zone border (as depicted in Figure B.24) on Kalimantan, Indonesia. All regressions include controls for age. Source: DHS.

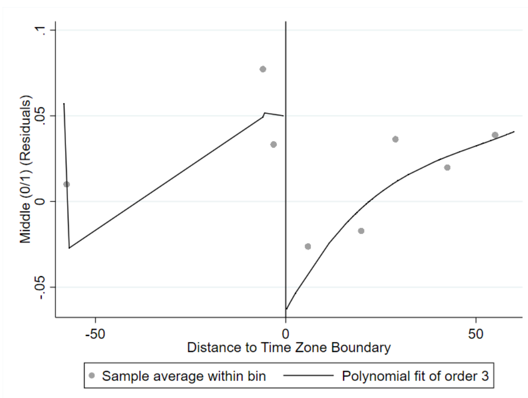
Figure B.28: Indonesia Regression Discontinuity Estimates: Effects of Later Sunset on Years of Schooling, Educational Attainment, and Enrollment (Polynomial Fit of Order 3)



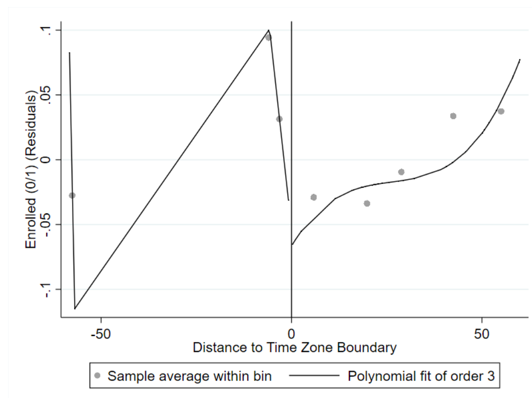
(a) Years of Schooling



(b) Primary School (0/1)



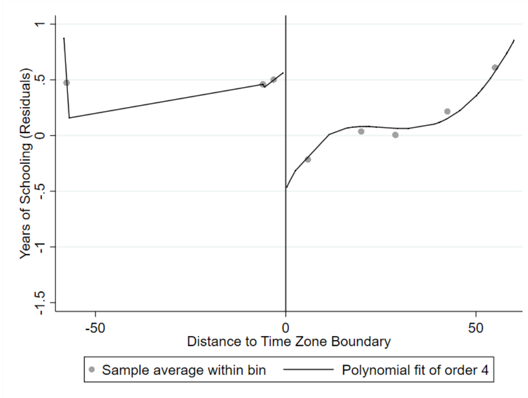
(c) Middle School (0/1)



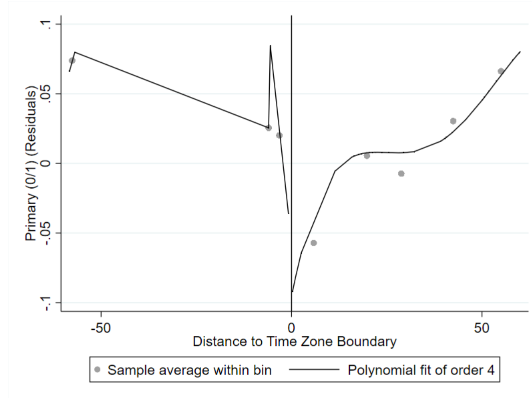
(d) Enrollment Status (0/1)

Notes: This figure presents the effects of annual average sunset time on years of schooling, educational attainment and enrollment for children between 6 and 16 years of age. I leverage discontinuity in annual average sunset time (Figure B.25) for DHS PSUs on either side of the time zone border (as depicted in Figure B.24) on Kalimantan, Indonesia. All regressions include controls for age. Source: DHS.

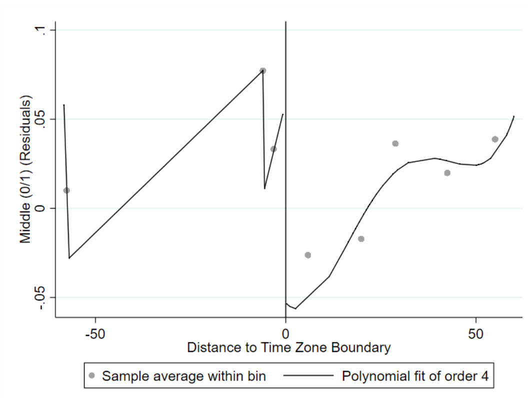
Figure B.29: Indonesia Regression Discontinuity Estimates: Effects of Later Sunset on Years of Schooling, Educational Attainment, and Enrollment (Polynomial Fit of Order 4)



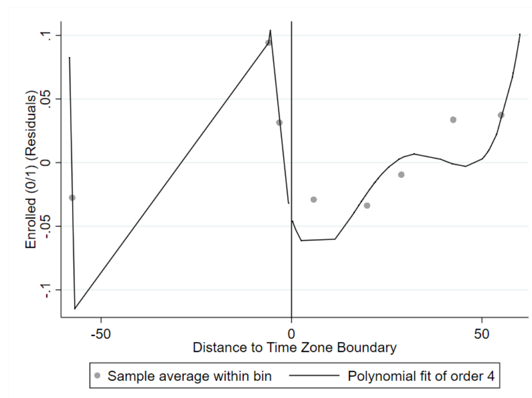
(a) Years of Schooling



(b) Primary School (0/1)



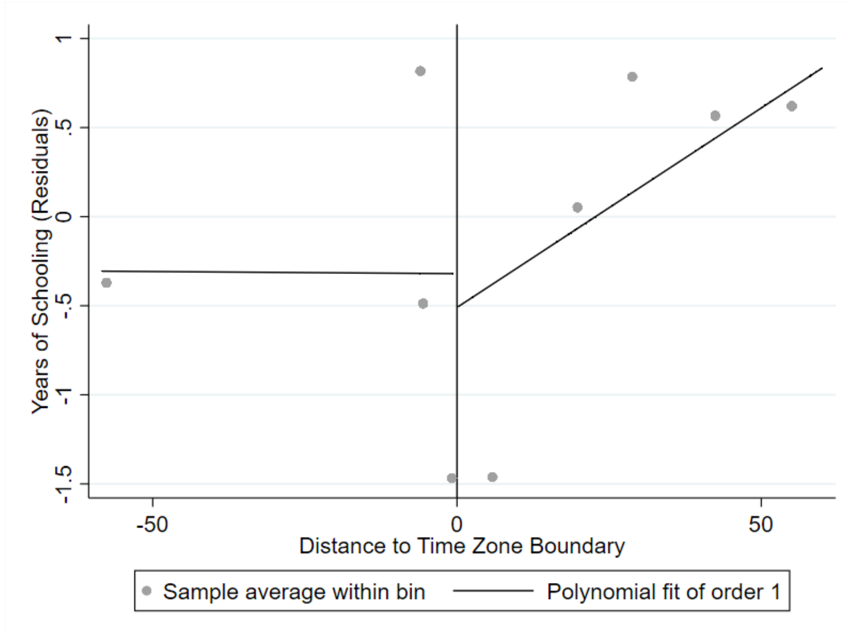
(c) Middle School (0/1)



(d) Enrollment Status (0/1)

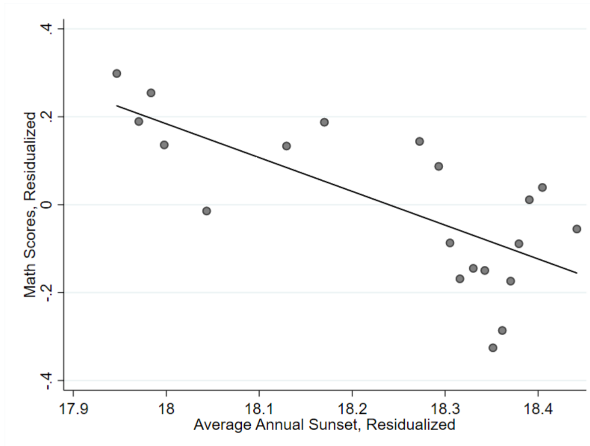
Notes: This figure presents the effects of annual average sunset time on years of schooling, educational attainment and enrollment for children between 6 and 16 years of age. I leverage discontinuity in annual average sunset time (Figure B.25) for DHS PSUs on either side of the time zone border (as depicted in Figure B.24) on Kalimantan, Indonesia. All regressions include controls for age. Source: DHS.

Figure B.30: Placebo Test: Effects of Later Sunset on Years of Schooling for Individuals Over 40 Years of Age (Polynomial Fit of Order 1)

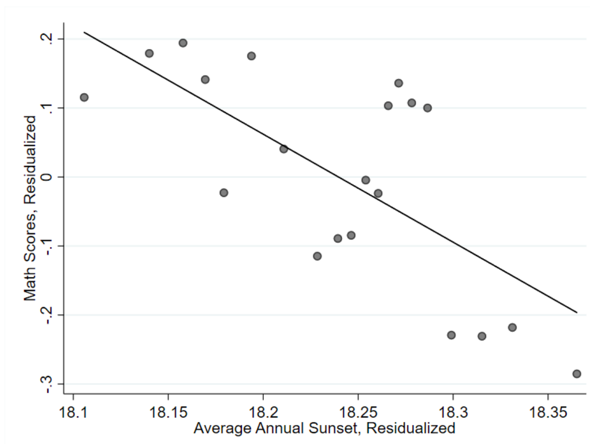


Notes: This figure presents the effects of annual average sunset time on years of schooling for adults over 40 years of age. I leverage discontinuity in annual average sunset time (Figure B.25) for DHS PSUs on either side of the time zone border (as depicted in Figure B.24) on Kalimantan, Indonesia. All regressions include controls for age. Source: DHS.

Figure B.31: Long-Run Effects of Late Sunset on Math Scores



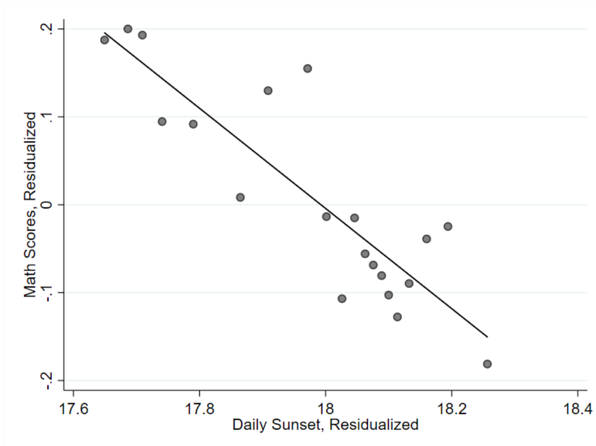
(a) Math Test Scores (Table B.59, Column 2)



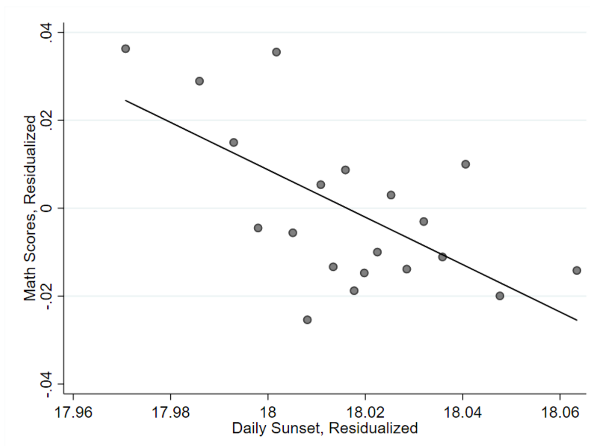
(b) Math Test Scores (Table B.59, Column 3)

Notes: This figure presents binned scatterplots for the relationship between annual average sunset time (24-hour clock) and children's math test scores in India. Figure (a) plots residuals for annual average sunset and math scores after absorbing week-of-year, day-of-week, and age fixed effects. Figure (b) plots residuals for annual average sunset and math scores after absorbing week-of-year, day-of-week, and age fixed effects as well as controlling for latitude and weather. Source: YLS.

Figure B.32: Short-Run Effects of Late Sunset on Math Scores



(a) Math Test Scores (Table B.60, Column 2)



(b) Math Test Scores (Table B.60, Column 3)

Notes: This figure presents binned scatterplots for the relationship between annual sunset time on the day of the test (24-hour clock) and children's math test scores in India. Figure (a) plots residuals for daily sunset time and math scores after absorbing week-of-year and age fixed effects and controlling for lagged test scores. Figure (b) plots residuals for annual average sunset and math scores after absorbing week-of-year, age, and child fixed effects. Source: YLS.

Table B.45: 45 Developing Countries: Effect of Late Sunset on Years of Schooling

	(1) Years of Schooling β / SE	(2) Years of Schooling β / SE	(3) Years of Schooling β / SE	(4) Years of Schooling β / SE
Annual Average Sunset Time (Hours)	-0.82***	-0.70***	-0.70***	-0.54***
	(0.01)	(0.01)	(0.01)	(0.01)
Age FE	No	Yes	Yes	Yes
Geographic Controls	No	No	Yes	Yes
Socioeconomic Indicators	No	No	No	Yes
Mean	3.16	3.16	3.16	3.22
Observations	2944329	2944329	2930533	2559105
R^2	0.012	0.506	0.507	0.592

Notes: This table presents the effect of annual average sunset time on years of schooling for children between 6 and 16 years of age across 45 countries in the developing world. Each column represents a separate regression estimating Equation (10) on years of schooling. Column 1 includes no controls, formally presenting the point estimate from Figure 3.1. Column 2 includes age fixed effects, Column 3 also includes controls for latitude and elevation at the PSU level, while Column 4 includes an additional control for household asset index and rural-urban status in addition to all the previous controls. Standard errors are in parentheses, clustered at the PSU level. Source: DHS.

Table B.46: Other Controls: Effect of Late Sunset on Years of Schooling, Educational Attainment, and Enrollment Status

	(1) Years of Schooling β / SE	(2) Primary (0/1) β / SE	(3) Middle (0/1) β / SE	(4) Enrolled (0/1) β / SE
Annual Average Sunset Time (Hours)	-0.93***	-0.13***	-0.09***	-0.12**
	(0.29)	(0.04)	(0.03)	(0.05)
Age FE	Yes	Yes	Yes	Yes
Geographic Controls	Yes	Yes	Yes	Yes
Socioeconomic Indicators	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Mean	4.44	0.48	0.21	0.90
Observations	638682	638682	638682	638682
R^2	0.738	0.647	0.565	0.113

Notes: This table presents the effect of annual average sunset time on years of schooling, likelihood of completing primary and middle school, and enrollment status for children between 6 and 16 years of age in India. Each column represents a separate regression estimating Equation (10) on the outcome variable. All regressions include age and district fixed effects, as well as controls for latitude, elevation at the PSU level and household asset index. Standard errors are in parentheses, clustered at the PSU level. Source: 2015 India DHS.

Table B.47: Age-Appropriate Sample: Effect of Late Sunset on Years of Schooling and Educational Attainment

	(1) Years of Schooling Age>8 β / SE	(2) Primary (0/1) Age>8 β / SE	(3) Years of Schooling Age>11 β / SE	(4) Middle (0/1) Age>11 β / SE
Annual Average Sunset Time (Hours)	-1.10***	-0.17***	-1.38***	-0.15**
	(0.39)	(0.06)	(0.49)	(0.07)
Age FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Mean	5.72	0.66	6.94	0.46
Observations	461850	461850	294088	294088
R^2	0.546	0.463	0.308	0.384

Notes: This table presents the effect of annual average sunset time on years of schooling and likelihood of completing primary and middle school for children between 6 and 16 years of age in India. Each column represents a separate regression estimating Equation (10) on the outcome variable. Columns 1 and 2 include children over 8 years of age. Columns 3 and 4 include children over 11 years of age. All regressions include district and age fixed effects. Standard errors are in parentheses, clustered at the PSU level. Source: 2015 India DHS.

Table B.48: Alternative Measure of Educational Attainment: Effect of Late Sunset on Educational Attainment

	(1)	(2)	(3)	(4)
	In/Completed Primary (0/1)	In/Completed Secondary (0/1)	In/Completed Primary (0/1)	In/Completed Secondary (0/1)
	Age>5	Age>5	Age>8	Age>11
	β / SE	β / SE	β / SE	β / SE
Annual Average Sunset Time (Hours)	-0.11**	-0.12***	-0.10***	-0.21***
	(0.04)	(0.04)	(0.04)	(0.08)
Age FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Mean	0.95	0.38	0.96	0.77
Observations	638682	638682	461850	294088
R^2	0.063	0.622	0.045	0.178

Notes: This table presents the effect of annual average sunset time on the likelihood that a child is in primary (secondary or post-primary) school or has completed primary (secondary or post-primary) school for children between 6 and 16 years of age in India. Each column represents a separate regression estimating Equation (10) on the outcome variable. Columns 3 and 4 include children over 8 and 11 years of age, respectively. All regressions include district and age fixed effects. Standard errors are in parentheses, clustered at the PSU level. Source: 2015 India DHS.

Table B.49: Dropping Wider Districts: Effect of Late Sunset on Years of Schooling, Educational Attainment, and Enrollment Status

	(1) Years of Schooling β / SE	(2) Primary (0/1) β / SE	(3) Middle (0/1) β / SE	(4) Enrolled (0/1) β / SE
Annual Average Sunset Time (Hours)	-0.80**	-0.13***	-0.05	-0.10*
	(0.38)	(0.05)	(0.04)	(0.06)
Age FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Mean	4.42	0.48	0.21	0.90
Observations	568519	568519	568519	568519
R^2	0.731	0.642	0.560	0.093

Notes: This table presents the effect of annual average sunset time on years of schooling, likelihood of completing primary and middle school, and enrollment status for children between 6 and 16 years of age in India. Each column represents a separate regression estimating Equation (10) on the outcome variable. All regressions include district and age fixed effects. I drop wider districts or districts where the difference in annual average sunset time between the easternmost and westernmost PSUs within a district is over the 90th percentile of the distribution presented in Figure B.23. Standard errors are in parentheses, clustered at the PSU level. Source: 2015 India DHS.

Table B.50: Only Wider Districts: Effect of Late Sunset on Years of Schooling, Educational Attainment, and Enrollment Status

	(1) Years of Schooling β / SE	(2) Primary (0/1) β / SE	(3) Middle (0/1) β / SE	(4) Enrolled (0/1) β / SE
Annual Average Sunset Time (Hours)	-0.96*	-0.11	-0.13**	-0.11
	(0.53)	(0.07)	(0.06)	(0.09)
Age FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Mean	4.57	0.50	0.22	0.90
Observations	70163	70163	70163	70163
R^2	0.735	0.658	0.573	0.093

Notes: This table presents the effect of annual average sunset time on years of schooling, likelihood of completing primary and middle school, and enrollment status for children between 6 and 16 years of age in India. Each column represents a separate regression estimating Equation (10) on the outcome variable. All regressions include district and age fixed effects. I only include wider districts or districts where the difference in annual average sunset time between the easternmost and westernmost PSUs within a district is over the 90th percentile of the distribution presented in Figure B.23. Standard errors are in parentheses, clustered at the PSU level. Source: 2015 India DHS.

Table B.51: Standard Errors Clustered at the District Level: Effect of Late Sunset on Years of Schooling, Educational Attainment, and Enrollment Status

	(1) Years of Schooling β / SE	(2) Primary (0/1) β / SE	(3) Middle (0/1) β / SE	(4) Enrolled (0/1) β / SE
Annual Average Sunset Time (Hours)	-0.86*	-0.13**	-0.08*	-0.11
	(0.45)	(0.06)	(0.04)	(0.07)
Age FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Mean	4.44	0.48	0.21	0.90
Observations	638682	638682	638682	638682
R^2	0.732	0.643	0.561	0.093

Notes: This table presents the effect of annual average sunset time on years of schooling, likelihood of completing primary and middle school, and enrollment status for children between 6 and 16 years of age in India. Each column represents a separate regression estimating Equation (10) on the outcome variable. All regressions include age and district fixed effects. Standard errors are in parentheses, clustered at the district level. Source: 2015 India DHS.

Table B.52: State Fixed Effects: Effect of Late Sunset on Years of Schooling, Educational Attainment, and Enrollment Status

	(1) Years of Schooling β / SE	(2) Primary (0/1) β / SE	(3) Middle (0/1) β / SE	(4) Enrolled (0/1) β / SE
Annual Average Sunset Time (Hours)	-0.25***	-0.03***	-0.02***	-0.13***
	(0.06)	(0.01)	(0.01)	(0.01)
Age FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Mean	4.44	0.48	0.21	0.90
Observations	638682	638682	638682	638682
R^2	0.719	0.636	0.555	0.065

Notes: This table presents the effect of annual average sunset time on years of schooling, likelihood of completing primary and middle school, and enrollment status for children between 6 and 16 years of age in India. Each column represents a separate regression estimating Equation (10) on the outcome variable. All regressions include age and state fixed effects. Standard errors are in parentheses, clustered at the PSU level. Source: 2015 India DHS.

Table B.53: State Fixed Effects (Other Controls): Effect of Late Sunset on Years of Schooling, Educational Attainment, and Enrollment Status

	(1) Years of Schooling β / SE	(2) Primary (0/1) β / SE	(3) Middle (0/1) β / SE	(4) Enrolled (0/1) β / SE
Annual Average Sunset Time (Hours)	-0.50***	-0.06***	-0.05***	-0.17***
	(0.05)	(0.01)	(0.01)	(0.01)
Age FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Geographic Controls	Yes	Yes	Yes	Yes
Socioeconomic Indicators	Yes	Yes	Yes	Yes
Mean	4.44	0.48	0.21	0.90
Observations	638682	638682	638682	638682
R^2	0.727	0.640	0.560	0.092

Notes: This table presents the effect of annual average sunset time on years of schooling, likelihood of completing primary and middle school, and enrollment status for children between 6 and 16 years of age in India. Each column represents a separate regression estimating Equation (10) on the outcome variable. All regressions include age and state fixed effects, as well as controls for latitude, elevation at the PSU level, rural-urban status and household asset index. Standard errors are in parentheses, clustered at the PSU level. Source: 2015 India DHS.

Table B.54: Did Surveyors Sample Younger Children in Places with Later Annual Average Sunset Times?

	(1) Age β / SE
Annual Average Sunset Time (Hours)	0.34
	(0.33)
District FE	Yes
Mean	10.99
Observations	638682
R^2	0.004

Notes: This table presents the effect of annual average sunset time on age for children between 6 and 16 years of age in India. The regression includes district fixed effects. Standard errors are in parentheses, clustered at the PSU level. Source: 2015 India DHS.

Table B.55: Indonesia Regression Discontinuity Estimates: Effects of Later Sunset on Years of Schooling, Educational Attainment, and Enrollment

	(1) Years of Schooling	(2) Primary (0/1)	(3) Middle (0/1)	(4) Enrolled (0/1)
Conventional	-0.654	-0.0392	-0.0727	-0.0527
Bias-corrected	-0.728	-0.0347	-0.0778	-0.0485
Robust	-0.728	-0.0347	-0.0778	-0.0485
Robust 95% CI	[-1.114 -.342]	[-.114 .045]	[-.151 -.005]	[-.145 .048]
Observations	3722	3722	3722	3722
Conventional p-value	0.000	0.284	0.031	0.225
Robust p-value	0.000	0.391	0.037	0.323
Order Loc. Poly. (p)	1.000	1.000	1.000	1.000
Order Bias (q)	2.000	2.000	2.000	2.000

Notes: This figure presents the effects of annual average sunset time on years of schooling, educational attainment and enrollment for children between 6 and 16 years of age. Each column represents a separate regression. All regressions include controls for age. The RD estimates are constructed using the epanechnikov kernel. The bandwidth choice mserd is an upgraded version of both the IK and the CCT implementations of the MSE-optimal bandwidth selectors discussed in (210) and (78), respectively. I use the code written by (77) for robust bias-corrected inference. Source: 2003 Indonesia DHS.

Table B.56: Indonesia Regression Discontinuity Estimates (Other Controls): Effects of Later Sunset on Years of Schooling, Educational Attainment, and Enrollment

	(1) Years of Schooling	(2) Primary (0/1)	(3) Middle (0/1)	(4) Enrolled (0/1)
Conventional	-0.674	-0.0533	-0.0824	-0.0900
Bias-corrected	-0.716	-0.0515	-0.0916	-0.101
Robust	-0.716	-0.0515	-0.0916	-0.101
Robust 95% CI	[-1.052 -.381]	[-.134 .031]	[-.163 -.004]	[-.198 -.021]
Geographic Controls	Yes	Yes	Yes	Yes
Socioeconomic Controls	Yes	Yes	Yes	Yes
Observations	3722	3722	3722	3722
Conventional p-value	0.000	0.148	0.012	0.043
Robust p-value	0.000	0.220	0.011	0.040
Order Loc. Poly. (p)	1.000	1.000	1.000	1.000
Order Bias (q)	2.000	2.000	2.000	2.000

Notes: This figure presents the effects of annual average sunset time on years of schooling, educational attainment and enrollment for children between 6 and 16 years of age. Each column represents a separate regression. All regressions include controls for age as well as socioeconomic and geographic indicators: latitude, altitude, electricity (0/1), radio (0/1), television (0/1), refrigerator (0/1), bicycle (0/1), motorcycle (0/1), car (0/1) and wealth index (1-5). The RD estimates are constructed using the epanechnikov kernel. The bandwidth choice mserd is an upgraded version of both the IK and the CCT implementations of the MSE-optimal bandwidth selectors discussed in (210) and (78), respectively. I use the code written by (77) for robust bias-corrected inference. Source: 2003 Indonesia DHS.

Table B.57: Indonesia Regression Discontinuity Estimates (Falsification Test): Effects of Later Sunset on Age and Sex

	(1) Household Head Age	(2) Child Sex	(3) Child Age
Conventional	0.417	-0.0219	0.338
Bias-corrected	0.0601	-0.0398	0.308
Robust	0.0601	-0.0398	0.308
Robust 95% CI	[-2.468 2.588]	[-.183 .104]	[-.570 1.186]
Observations	3722	3722	3722
Conventional p-value	0.720	0.739	0.396
Robust p-value	0.963	0.587	0.491
Order Loc. Poly. (p)	1.000	1.000	1.000
Order Bias (q)	2.000	2.000	2.000

Notes: This figure presents the effects of annual average sunset time on age of household head, child sex and child age for children between 6 and 16 years of age. Each column represents a separate regression. The RD estimates are constructed using the epanechnikov kernel. The bandwidth choice mserd is an upgraded version of both the IK and the CCT implementations of the MSE-optimal bandwidth selectors discussed in (210) and (78), respectively. I use the code written by (77) for robust bias-corrected inference. Source: 2003 Indonesia DHS.

Table B.58: Placebo Test: Effects of Later Sunset on Years of Schooling for Individuals Over 40 Years of Age

	(1) Years of Schooling
Conventional	0.0107
Bias-corrected	-0.1220
Robust	-0.1220
Robust 95% CI	[-.899 .655]
Observations	3266
Conventional p-value	0.977
Robust p-value	0.758
Order Loc. Poly. (p)	1.000
Order Bias (q)	2.000

Notes: This figure presents the effects of annual average sunset time on years of schoolingfor adults over 40 years of age. All regressions include controls for age. The RD estimates are constructed using the epanechnikov kernel. The bandwidth choice mserd is an upgraded version of both the IK and the CCT implementations of the MSE-optimal bandwidth selectors discussed in (210) and (78), respectively. I use the code written by (77) for robust bias-corrected inference. Source: 2003 Indonesia DHS.

Table B.59: Long-Run Effects of Late Sunset on Math Test Scores

	(1) Math (SD) β / SE	(2) Math (SD) β / SE	(3) Math (SD) β / SE
Annual Average Sunset Time (Hours)	-0.812***	-0.769***	-1.565***
	(0.096)	(0.097)	(0.217)
Age Dummies	Yes	Yes	Yes
Week-of-Year FE	No	Yes	Yes
Day of Week FE	No	Yes	Yes
Latitude	No	No	Yes
Weather Controls	No	No	Yes
Observations	7511	7511	7511
R^2	0.018	0.048	0.080

Notes: This table presents the effect of annual average sunset time on math scores for school-age children. Each column represents a separate regression. All regressions include age (year/round) fixed effects. Column 2 includes week-of-year and day-of-week fixed effects. Column 3 includes week-of-year and day-of-week fixed effects as well as controls for latitude and weather. Standard errors are in parentheses, clustered at the child level. Source: YLS.

Table B.60: Short-Run Effects of Late Sunset on Math Test Scores

	(1) Math (SD) β / SE	(2) Math (SD) β / SE	(3) Math (SD) β / SE	(4) Math (SD) β / SE
Daily Sunset Time (Hours)	-0.627***	-0.570***	-0.539	-0.468
	(0.088)	(0.062)	(0.413)	(0.423)
L.Math		0.645***		
		(0.011)		
Age Dummies	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Child FE	No	No	Yes	Yes
Day of Week FE	No	No	No	Yes
Weather Controls	No	No	No	Yes
Observations	7511	4589	7511	7511
R^2	0.045	0.439	0.778	0.782

Notes: This table presents the effect of day-of-test sunset time on math scores for school-age children. Each column represents a separate regression. All regressions include age (year/round) and week-of-year fixed effects. Column 2 includes controls for lagged test scores. Column 3 includes child fixed effects. Column 4 includes child and day-of-week fixed effects as well as controls for weather. Standard errors are in parentheses, clustered at the child level. Source: YLS.

Table B.61: Falsification Test: Short-Run Effects of Past and Future Day-of-Test Sunset Time on Current Survey Round Math Test Scores

	(1) Math (SD) β / SE
Daily Sunset Time (Hours)	-0.692***
	(0.136)
L.Daily Sunset Time (Hours)	0.134
	(0.098)
F.Daily Sunset Time (Hours)	0.010
	(0.090)
L.Math	0.637***
	(0.018)
Age Dummies	Yes
Week-of-Year FE	Yes
Observations	1834
R^2	0.412

Notes: This table presents the effect of sunset time on the previous survey round test date and sunset time on the next survey round test date on math scores in the current survey round for school-age children. The regression include age (year/round) and week-of-year fixed effects as well as controls for lagged test scores. Standard errors are in parentheses, clustered at the child level. Source: YLS.

REDS: Effect of Later Sunset on Academic Outcomes

Here, I use a nationally representative survey of rural households in India, the 2006 Rural Economic and Demographic Survey or REDS, to investigate the associated effects of later sunset on educational outcomes for school-age children. Analogous to the 2015 Indian DHS specification, I exploit plausibly exogenous cross-sectional variation in annual average sunset time at the village level within districts. As before, I find that an hour delay in annual average sunset time reduces schooling among school-age children, translating into lower educational attainment at the primary and middle school level (Table B.62). Furthermore, an hour delay in annual average sunset time reduces the likelihood of current school enrollment by 17 percentage points, or equivalently, a one standard deviation delay in annual average sunset time reduces the likelihood of current school enrollment by 10%.

If wealthier households sort themselves into villages with earlier annual average sunset, my baseline estimates may be confounded by residential sorting. However, if sorting were occurring, one might expect villages that observe later sunset to have low in-migration and more out-migration. I examine the relationship between later sunset and episodes of in- and out-migration at the village level (Table B.63). I fail to find evidence that villages that observe later sunset have more episodes of out-migration or fewer episodes of in-migration. Moreover, I fail to find evidence for a negative relationship between sunset time and instances of non-residents migrating to work to villages.

In Tables B.64 and B.65, I control for village level geographic characteristics like elevation, latitude, temperature and rainfall as well as child level biological characteristics like height, weight and sex. I also control for episodes of in- and out-migration experienced at the village level in the last 50 years, access to water and electricity as well as other street level attributes such as availability of street lighting or proportion of households with an indoor toilet. My baseline estimates remain relatively unaffected. In Tables B.66 - B.69, I examine the relationship between annual average sunset and household and village level observables. I find a statistically significant relationship for 2 out of 21 characteristics.[10]

These tests imply that any unobservable omitted variable that generates bias in my estimates must be orthogonal to these observables, but co-vary system-

[10]In Table B.70 I adjust standard errors to reflect spatial dependence as modeled in (103), and implemented by (202). I allow errors to be spatially auto-correlated within a distance of 500 km. The point estimates remain precisely estimated.

atically with both annual average sunset time and educational outcomes across the east-west gradient within a district. Given the richness of the observables, the existence of such unobservable omitted variables seems implausible.

Children's Wages

As a complement to the effects on educational outcomes and a robustness check on the underlying conceptual framework, I examine the relationship between sunset times and wages paid to child laborers. My time use results suggest that sleep is productivity-enhancing, increasing the marginal returns to study effort for students, and the marginal product of work effort for child laborers. Thus, if children are paid their marginal product, by reducing labor productivity later sunset must decrease marginal wages to disincentivize work effort from child laborers.

I test this prediction using village-by-industry level REDS data on daily wage rate paid to child laborers. Indeed, I find that an hour delay in annual average sunset time reduces the wage rate for children by roughly INR 24 (Table B.71).[11]

[11] Alternatively, by increasing dropouts, later sunset may increase the supply of child labor at the village level, in turn reducing children's wage rate. Because the estimates are at the village level I cannot rule such a general equilibrium effect.

Table B.62: Effect of Late Sunset on Years of Schooling, Educational Attainment, and Enrollment

	(1) Years of Schooling β / SE	(2) Primary (0/1) β / SE	(3) Middle (0/1) β / SE	(4) Enrolled (0/1) β / SE
Annual Average Sunset Time (Hours)	-1.06	-0.13	-0.17**	-0.17**
	(0.71)	(0.09)	(0.07)	(0.08)
Age Dummies	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Mean	4.79	0.52	0.23	0.91
Observations	10006	10006	10006	9192
R^2	0.663	0.650	0.574	0.117

Notes: This table presents the effect of annual average sunset time on years of schooling, educational attainment and enrollment status for children between 6 and 16 years of age in India. Each column represents a separate regression estimating Equation (10) on the outcome variable. All regressions include district and age fixed effects. Standard errors are in parentheses, clustered at the village level. Source: REDS.

Table B.63: Effect of Late Sunset on Migration

	(1) No. Times In-Migration: 50 yrs β / SE	(2) No. Times Out-Migration: 50 yrs β / SE	(3) Non-Residents In-Migrate for Work 10 years: (0/1) β / SE
Annual Average Sunset Time (Hours)	10.93	-5.00	0.06
	(13.23)	(3.54)	(0.67)
District FE	Yes	Yes	Yes
Mean	7.27	2.01	0.71
Observations	190	158	204
R^2	0.813	0.912	0.709

Notes: This table presents the effect of annual average sunset time on episodes of in-migration and out-migration in the last 50 years as well as on the likelihood of in-migration for work in the last 10 years, both at the village level. Each column represents a separate regression. All regressions include district fixed effects. Heteroskedasticity robust standard errors are in parentheses. Source: REDS.

Table B.64: Controlling for Geographic and Individual Level Observables: Effect of Late Sunset on Years of Schooling, Educational Attainment and Enrollment

	(1) Years of Schooling β / SE	(2) Primary (0/1) β / SE	(3) Middle (0/1) β / SE	(4) Enrolled (0/1) β / SE
Annual Average Sunset Time (Hours)	-0.87	-0.13	-0.14*	-0.14*
	(0.78)	(0.10)	(0.07)	(0.08)
Latitude	-0.10	-0.00	-0.01	0.00
	(0.08)	(0.01)	(0.01)	(0.01)
Elevation	-0.00**	-0.00	-0.00**	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Rain	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Temperature	-0.15**	-0.01	-0.01**	-0.02***
	(0.07)	(0.01)	(0.01)	(0.01)
Log Height	0.29**	0.03*	0.02	-0.04**
	(0.13)	(0.02)	(0.02)	(0.02)
Log Weight	0.20*	0.00	0.02	0.04**
	(0.11)	(0.02)	(0.01)	(0.02)
Male (0/1)	0.30***	0.02***	0.03***	0.03***
	(0.05)	(0.01)	(0.01)	(0.01)
Age Dummies	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Mean	4.79	0.52	0.23	0.91
Observations	10006	10006	10006	9192
R^2	0.666	0.651	0.575	0.122

Notes: This table presents the effect of annual average sunset time on years of schooling, educational attainment and enrollment status for children between 6 and 16 years of age. Each column represents a separate regression estimating Equation (10) on the outcome variable. All regressions include district and age fixed effects, and controls for latitude, elevation, rain, temperature, height, weight and sex. Standard errors are in parentheses, clustered at the village level. Source: REDS.

Table B.65: Controlling for Household and Village Level Observables: Effect of Late Sunset on Years of Schooling, Educational Attainment, and Enrollment

	(1) Years of Schooling β / SE	(2) Primary (0/1) β / SE	(3) Middle (0/1) β / SE	(4) Enrolled (0/1) β / SE
Annual Average Sunset Time (Hours)	-1.44**	-0.18**	-0.25***	-0.32***
	(0.69)	(0.07)	(0.08)	(0.08)
No. Times In-Migration 50 yrs	-0.00	-0.00	-0.00	-0.00**
	(0.01)	(0.00)	(0.00)	(0.00)
No. Times Out-Migration 50 yrs	0.02	0.00	0.00	-0.00
	(0.02)	(0.00)	(0.00)	(0.00)
In-Migration for Work in 10 years (0/1)	0.55***	0.06***	0.04*	0.03**
	(0.15)	(0.02)	(0.02)	(0.01)
Permanent Road (0/1)	-0.03	-0.01	-0.01	0.00
	(0.08)	(0.01)	(0.01)	(0.01)
Brick Houses (Prop.)	-0.05	0.01	-0.04	0.07
	(0.47)	(0.07)	(0.06)	(0.06)
Huts (Prop.)	-1.69*	-0.16	-0.09	-0.11
	(0.95)	(0.15)	(0.11)	(0.12)
Mud Houses (Prop.)	-0.29	-0.03	-0.03	0.01
	(0.36)	(0.05)	(0.04)	(0.04)
Multi-Storeyed Houses (Prop.)	0.02	-0.07	0.16	0.09
	(0.92)	(0.11)	(0.15)	(0.14)
Public Tap (0/1)	0.05	-0.01	0.02	-0.00
	(0.08)	(0.01)	(0.01)	(0.01)
Wells (0/1)	-0.27**	-0.02	-0.04***	-0.02
	(0.11)	(0.01)	(0.01)	(0.01)
HHs Running Water (Prop.)	0.50	0.04	0.01	0.03
	(0.54)	(0.07)	(0.06)	(0.04)
Street Lights (0/1)	0.27*	0.04**	-0.00	-0.02
	(0.14)	(0.02)	(0.02)	(0.02)
HHs Electricity (Prop.)	0.09	0.05	0.02	-0.04
	(0.46)	(0.06)	(0.06)	(0.05)
Public Toilet (0/1)	-0.22	-0.01	-0.04***	-0.00
	(0.17)	(0.03)	(0.01)	(0.02)
HHs Indoor Toilet (Prop.)	-0.15	0.02	-0.12**	-0.10*
	(0.52)	(0.07)	(0.05)	(0.05)
HHs Landline (Prop.)	0.56	0.04	0.01	-0.03
	(1.12)	(0.14)	(0.18)	(0.13)
HHs Large Livestock (Prop.)	-0.58***	-0.07***	0.01	-0.04
	(0.19)	(0.02)	(0.02)	(0.03)
HHs Bicycle (Prop.)	1.04***	0.12***	0.06**	-0.01
	(0.29)	(0.04)	(0.03)	(0.03)
HHs Mobile (Prop.)	0.12	-0.04	-0.12**	0.00
	(0.44)	(0.08)	(0.05)	(0.05)
HHs Motorcycle (Prop.)	-0.20	-0.02	0.11*	0.09
	(0.55)	(0.06)	(0.06)	(0.06)
HHs Car (Prop.)	2.48**	0.21	0.32*	0.33***
	(1.07)	(0.15)	(0.17)	(0.12)
Age Dummies	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Mean	4.63	0.50	0.22	0.91
Observations	7601	7601	7601	6914
R^2	0.650	0.641	0.555	0.111

Notes: This table presents the effect of annual average sunset time on years of schooling for children between 6 and 16 years of age. Each column represents a separate regression estimating Equation (10) on the outcome variable. All regressions include district and age fixed effects, and controls for migration and village infrastructure. Standard errors are in parentheses, clustered at the village level. Source: REDS.

Table B.66: Effect of Late Sunset on Observables I

	(1) Log Height	(2) Log Weight	(3) Male (0/1)	(4) Permanent Road (0/1)	(5) Brick Houses (Prop.)	(6) Huts (Prop.)
	β / SE	β / SE	β / SE	β / SE	β / SE	β / SE
Annual Average Sunset Time (Hours)	0.07	-0.14	-0.01	-0.37	-0.09	-0.00
	(0.09)	(0.13)	(0.09)	(0.93)	(0.11)	(0.03)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean	1.26	3.35	0.54	0.43	0.14	0.03
Observations	10080	10080	10080	9491	9244	9244
R^2	0.059	0.088	0.020	0.520	0.755	0.643

Notes: This table presents the effect of annual average sunset time on household and village level observables. Each column represents a separate regression estimating Equation (10) on the outcome variable. All regressions include district fixed effects. Standard errors are in parentheses, clustered at the village level. Source: REDS.

Table B.67: Effect of Late Sunset on Observables II

	(1) Mud Houses (Prop.)	(2) Multi-Storeyed Houses (Prop.)	(3) Public Tap (0/1)	(4) Wells (0/1)	(5) HHs Running Water (Prop.)
	β / SE	β / SE	β / SE	β / SE	β / SE
Annual Average Sunset Time (Hours)	-0.37*	0.06	-0.80**	-0.77	0.08
	(0.20)	(0.07)	(0.37)	(0.71)	(0.07)
District FE	Yes	Yes	Yes	Yes	Yes
Mean	0.12	0.02	0.41	0.40	0.05
Observations	9244	9244	9491	9491	9244
R^2	0.702	0.576	0.748	0.660	0.598

Notes: This table presents the effect of annual average sunset time on household and village level observables. Each column represents a separate regression estimating Equation (10) on the outcome variable. All regressions include district fixed effects. Standard errors are in parentheses, clustered at the village level. Source: REDS.

Table B.68: Effect of Late Sunset on Observables III

	(1) Street Lights (0/1) β / SE	(2) HHs Electricity (Prop.) β / SE	(3) Public Toilet (0/1) β / SE	(4) HHs Indoor Toilet (Prop.) β / SE	(5) HHs Landline (Prop.) β / SE
Annual Average Sunset Time (Hours)	0.07	-0.01	-0.16	-0.03	0.06
	(0.25)	(0.14)	(0.19)	(0.09)	(0.06)
District FE	Yes	Yes	Yes	Yes	Yes
Mean	0.36	0.13	0.10	0.07	0.03
Observations	9491	9244	9491	9244	9244
R^2	0.877	0.656	0.575	0.545	0.817

Notes: This table presents the effect of annual average sunset time on household and village level observables. Each column represents a separate regression estimating Equation (10) on the outcome variable. All regressions include district fixed effects. Standard errors are in parentheses, clustered at the village level. Source: REDS.

Table B.69: Effect of Late Sunset on Observables IV

	(1) HHs Large Livestock (Prop.) β / SE	(2) HHs Bicycle (Prop.) β / SE	(3) HHs Mobile (Prop.) β / SE	(4) HHs Motorcycle (Prop.) β / SE	(5) HHs Car (Prop.) β / SE
Annual Average Sunset Time (Hours)	0.12	-0.08	-0.03	-0.02	-0.00
	(0.14)	(0.22)	(0.06)	(0.04)	(0.01)
District FE	Yes	Yes	Yes	Yes	Yes
Mean	0.22	0.24	0.05	0.05	0.01
Observations	9244	9244	9244	9244	9244
R^2	0.663	0.740	0.606	0.594	0.396

Notes: This table presents the effect of annual average sunset time on household and village level observables. Each column represents a separate regression estimating Equation (10) on the outcome variable. All regressions include district fixed effects. Standard errors are in parentheses, clustered at the village level. Source: REDS.

Table B.70: Conley Standard Errors: Effect of Late Sunset on Years of Schooling, Educational Attainment, and Enrollment

	(1) Years of Schooling β / SE	(2) Primary (0/1) β / SE	(3) Middle (0/1) β / SE	(4) Enrolled (0/1) β / SE
Annual Average Sunset Time (Hours)	-1.06*	-0.13*	-0.17**	-0.17**
	(0.55)	(0.08)	(0.07)	(0.07)
Age Dummies	Yes	Yes	Yes	Yes
Observations	10006	10006	10006	9192
R^2	0.634	0.629	0.554	0.085

Notes: This table presents the effect of annual average sunset time on years of schooling, educational attainment and enrollment status for children between 6 and 16 years of age. Each column represents a separate regression estimating Equation (10) on the outcome variable. All regressions include district and age fixed effects. Standard errors are adjusted to reflect spatial dependence as modeled in (103). Spatial autocorrelation is assumed to linearly decrease in distance up to a cutoff of 500 km. Source: REDS.

Table B.71: Effect of Late Sunset on Children's Daily Wage Rate

	(1) Child Wage (INR) β / SE
Annual Average Sunset Time (Hours)	-24.38***
	(9.02)
District FE	Yes
Industry FE	Yes
Place FE	Yes
Geographic Controls	Yes
Mean	36.05
Observations	2434
R^2	0.544

Notes: This table presents the effect of annual average sunset time on children's daily wage rate by industry at the village level. Each column represents a separate regression. All regressions include district, industry, and place (inside or outside the village) fixed effects, and geographic controls: latitude, rainfall, temperature and elevation. Daily wage rates are winsorized at the 1% level. Standard errors are in parentheses, clustered at the village level. Source: REDS.

B.4 Appendix: Adults' Time Use

Table B.72: Effect of Late Sunset on Adults' Time Investment in Children (Hours)

	(1) Children 6-16 β / SE	(2) Children 6-10 β / SE	(3) Children 11-16 β / SE	(4) Multiple Children β / SE
Sunset Time (Hours)	0.09	0.05	0.11*	0.08
	(0.06)	(0.08)	(0.06)	(0.07)
District FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	0.41	0.56	0.22	0.42
Observations	21745	12035	9710	17274
R^2	0.026	0.038	0.033	0.028

Notes: This table presents the effect of daily sunset time on time allocated to children (in hours) by individuals over 16 years of age on weekdays in India. Each column represents a separate regression estimating Equation (8) on adults' time investment in children. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.73: State-by-Season FE: Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE	(5) HH Chores β / SE	(6) Time With Kids β / SE
Sunset Time (Hours)	-0.66***	0.04	0.79*	0.01	-0.13	-0.03
	(0.19)	(0.07)	(0.43)	(0.45)	(0.24)	(0.09)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State-by-Season FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean	8.11	0.11	7.06	5.40	2.72	0.43
Observations	48804	48804	48804	48804	48804	48804
R^2	0.081	0.014	0.046	0.028	0.019	0.023

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure, work, home production and time spent with children by adults on weekdays in India. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district, week-of-year and state-by-season fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.74: Latitude-by-Week-of-Year FE: Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE	(5) HH Chores β / SE	(6) Time With Kids β / SE
Sunset Time (Hours)	-0.91***	-0.05	0.78**	0.08	0.06	0.15*
	(0.18)	(0.05)	(0.33)	(0.35)	(0.18)	(0.08)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Latitude-by-Week-of-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean	8.11	0.11	7.06	5.40	2.72	0.43
Observations	48804	48804	48804	48804	48804	48804
R^2	0.085	0.014	0.047	0.028	0.020	0.024

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure, work, home production and time spent with children by adults on weekdays in India. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district, week-of-year and latitude-by-week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.75: District-by-Season FE: Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE	(5) HH Chores β / SE	(6) Time With Kids β / SE
Sunset Time (Hours)	-0.44**	0.05	0.35	0.23	-0.18	-0.05
	(0.19)	(0.08)	(0.48)	(0.49)	(0.25)	(0.10)
District-by-Season FE	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean	8.11	0.11	7.06	5.40	2.72	0.43
Observations	48804	48804	48804	48804	48804	48804
R^2	0.111	0.019	0.061	0.037	0.025	0.031

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure, work, home production and time spent with children by adults on weekdays in India. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district, week-of-year and district-by-season fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

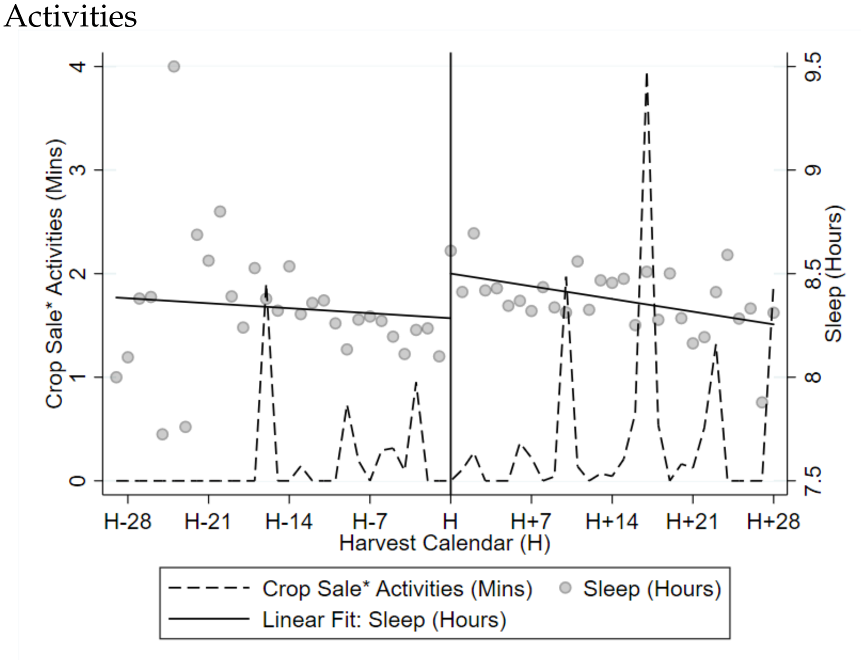
Table B.76: Effect of Late Sunset on Sleep and Nap for Adults

	(1) Sleep β / SE	(2) Nap β / SE	(3) Sleep and Nap β / SE
Sunset Time (Hours)	-0.50***	0.26***	-0.24**
	(0.10)	(0.08)	(0.12)
District FE	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes
Mean	8.11	0.45	8.57
Observations	48804	48804	48804
R^2	0.078	0.138	0.072

Notes: This table presents the effect of daily sunset time on sleep for individuals over 16 years of age on weekdays in India. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

B.5 Appendix: Can Poverty Help Explain Why Households Fail to Adjust?

Figure B.33: Crop Cultivator Households: Relationship Between the Pre- and Post-Harvest Period, Sleep, and Time Allocated to Crop Sale (and Purchase) Related Activities



Notes: This figure presents the relationship between the pre- and post-harvest period, sleep, and time allocated to crop sale (and purchase) related activities on weekdays for crop cultivator households. H-28, H-21, H-14, and H-7 denote dates in the pre-harvest month (approximately) 28, 21, 14, and 7 days away from the harvest date H, respectively. While H+7, H+14, H+21, and H+28 denote dates in post-harvest month (approximately) 7, 14, 21, and 28 days after the harvest date H. Source: ITUS.

Table B.77: Heterogeneity by Correlates of Poverty: Effect of Late Sunset on Sleep (Hours), Disaggregated by Age

	(1) Sleep β / SE	(2) Sleep β / SE	(3) Sleep β / SE	(4) Sleep β / SE
Adults				
Sunset Time (Hours)	-0.44***	-0.38***	-0.44***	-0.41***
	(0.10)	(0.10)	(0.10)	(0.10)
Sunset Time*Temporary House Structure (0/1)	-0.10**			
	(0.04)			
Sunset Time*Rural (0/1)		-0.19***		
		(0.05)		
Sunset Time*No Primary Education (0/1)			-0.09***	
			(0.03)	
Sunset Time*HH Expenditure∈(50p,75p)				-0.11**
				(0.05)
Sunset Time*HH Expenditure∈(25p,50p)				-0.07
				(0.04)
Sunset Time*HH Expenditure∈(0p,25p)				-0.14***
				(0.04)
Mean	8.11	8.11	8.11	8.11
Observations	48804	48804	48804	48804
R^2	0.086	0.089	0.089	0.090
Children				
Sunset Time (Hours)	-0.39***	-0.37**	-0.37***	-0.42***
	(0.15)	(0.15)	(0.14)	(0.14)
Sunset Time*Temporary House Structure (0/1)	-0.13**			
	(0.05)			
Sunset Time*Rural (0/1)		-0.15**		
		(0.07)		
Sunset Time*No Primary Education (0/1)			-0.14***	
			(0.04)	
Sunset Time*HH Expenditure∈(50p,75p)				-0.04
				(0.06)
Sunset Time*HH Expenditure∈(25p,50p)				-0.04
				(0.07)
Sunset Time*HH Expenditure∈(0p,25p)				-0.19***
				(0.07)
Mean	9.07	9.07	9.07	9.07
Observations	13964	13964	13964	13964
R^2	0.104	0.107	0.141	0.108
District FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes

Notes: This table presents the heterogeneous effect of daily sunset time on time allocated to sleep by correlates of socioeconomic status on weekdays for all individuals over the age of 6 in India. Panel 'Adults' includes all individuals over the age of 16. Panel 'Children' includes all individuals between 6 and 16 years of age. Each panel-column combination represents a separate regression. Column 1 shows the effect of daily sunset time on sleep for households that live in a temporary house structure compared to households that live in a permanent house structure. Column 2 shows the effect of daily sunset time on sleep for households living in rural areas compared to households living in urban areas. Column 3 shows the effect of daily sunset time on sleep for individuals that have completed primary education compared to individuals that have not completed primary education. Column 4 shows the effect of daily sunset time on sleep for households with average monthly expenditure below the 25th percentile, between 25th and 50th percentile, and between 50th and 75th percentile, compared to households with average monthly expenditure above the 75th percentile. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.78: Heterogeneity by Electrification (Night Lights): Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE
Sunset Time (Hours)	-0.38**	-0.53**	1.64***	0.04
	(0.15)	(0.23)	(0.40)	(0.33)
Sunset Time*Night Lights∈(0p,50p)	-0.16**	-0.23**	-0.01	0.09
	(0.07)	(0.11)	(0.16)	(0.17)
District FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	9.08	1.50	7.61	2.05
Observations	13851	13851	13851	13851
R^2	0.092	0.170	0.296	0.071

Notes: This table presents the heterogeneous effect of daily sunset time on time allocated to sleep, study, leisure and work (in hours) by electrification status at the district level (as proxied by nighttime lights intensity in 2001) on weekdays for children between 6 and 16 years of age on weekdays in India. Each column represents a separate regression. All regressions include district and week-of-year fixed effects. Unfortunately, I do not have nighttime lights data for one district in the ITUS sample. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.79: Crop Cultivator Households: Effect of Late Sunset on Children vs. Adults' Bedtimes and Wake-up Times (Hours) in Pre- vs. Post-Harvest Month

	(1) Bedtime β / SE	(2) Bedtime β / SE	(3) Wake-up Time β / SE	(4) Wake-up Time β / SE
Cultivator Households: Adults				
Sunset Time (Hours)	0.40**	0.23	0.54***	0.59***
	(0.18)	(0.19)	(0.15)	(0.18)
Sunset Time*Pre-Harvest	0.19	0.27*	-0.24**	-0.11
	(0.16)	(0.15)	(0.12)	(0.12)
Mean	21.54	21.54	5.77	5.77
Observations	8390	8390	8416	8416
R^2	0.224	0.238	0.220	0.234
Cultivator Households: Children				
Sunset Time (Hours)	0.47*	0.35	-0.01	-0.00
	(0.25)	(0.25)	(0.22)	(0.23)
Sunset Time*Pre-Harvest	0.07	0.02	-0.17	-0.06
	(0.19)	(0.19)	(0.14)	(0.15)
Mean	21.18	21.18	6.40	6.40
Observations	2354	2354	2362	2362
R^2	0.211	0.234	0.326	0.349
District FE	Yes	Yes	Yes	Yes
Month FE	Yes	No	Yes	No
Week-of-Year FE	No	Yes	No	Yes

Notes: This table presents the effect of daily sunset time on bedtimes and wake-up times before harvest compared to after harvest on weekdays for crop cultivator households in India. Panel 'Adults' includes all individuals over the age of 16. Panel 'Children' includes all individuals between 6 and 16 years of age. Each panel-column combination represents a separate regression estimating Equation (11) on the outcome variable. The interaction term captures the effect of an hour delay in daily sunset time for crop cultivator households in the pre-harvest month compared to the post-harvest month. All regressions include district fixed effects. Columns 1 and 3 include month fixed effects while Columns 2 and 4 include week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.80: Crop Cultivator Households: Effect of Late Sunset on Adults' Sleep (Hours) for Households with No School-Age Children vs. Households with School-Age Children in Pre- vs. Post-Harvest Month

	(1) Sleep No School-Age Child β / SE	(2) Sleep School-Age Child β / SE
Sunset Time (Hours)	0.34	-0.20
	(0.32)	(0.37)
Sunset Time*Pre-Harvest	-0.53***	-0.30
	(0.19)	(0.25)
District FE	Yes	Yes
Week-of-Year FE	Yes	Yes
Mean	8.24	8.16
Observations	4666	3794
R^2	0.141	0.216

Notes: This table presents the effect of daily sunset time on time allocated to sleep before harvest compared to after harvest on weekdays for crop cultivators over 16 years of age with no school-age children vs. crop cultivator adults with school-age children on weekdays in India. The interaction term captures the effect of an hour delay in daily sunset time for crop cultivator households in the pre-harvest month compared to the post-harvest month. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.81: Crop Cultivator Households (Controlling for Work Hours): Effect of Late Sunset on Individuals' Sleep (Hours) in Pre- vs. Post-Harvest Month

	(1) Sleep β / SE	(2) Sleep β / SE	(3) Sleep β / SE
All			
Sunset Time (Hours)	-0.70***	-0.12	-0.08
	(0.14)	(0.23)	(0.26)
Sunset Time*Pre-Harvest	-0.24***	-0.40**	-0.31*
	(0.09)	(0.19)	(0.18)
Mean	8.42	8.42	8.42
Observations	10827	10827	10827
R^2	0.145	0.149	0.159
Adults			
Sunset Time (Hours)	-0.66***	-0.03	0.14
	(0.15)	(0.25)	(0.29)
Sunset Time*Pre-Harvest	-0.25**	-0.42**	-0.38**
	(0.10)	(0.21)	(0.18)
Mean	8.20	8.20	8.20
Observations	8460	8460	8460
R^2	0.142	0.147	0.159
Children			
Sunset Time (Hours)	-0.70***	-0.48	-0.55
	(0.19)	(0.36)	(0.43)
Sunset Time*Pre-Harvest	-0.19	-0.31	-0.15
	(0.12)	(0.29)	(0.27)
Mean	9.19	9.19	9.19
Observations	2367	2367	2367
R^2	0.146	0.157	0.173
District FE	Yes	Yes	Yes
Season FE	Yes	No	No
Month FE	No	Yes	No
Week-of-Year FE	No	No	Yes

Notes: This table presents the effect of daily sunset time on time allocated to sleep before harvest compared to after harvest on weekdays for crop cultivator households in India. Panel 'All' includes all individuals over the age of 6. Panel 'Adults' includes all individuals over the age of 16. Panel 'Children' includes all individuals between 6 and 16 years of age. Each panel-column combination represents a separate regression estimating Equation (11) on the outcome variable. The interaction term captures the effect of an hour delay in daily sunset time for crop cultivator households in the pre-harvest month compared to the post-harvest month. All regressions include district fixed effects and control for work hours. Column 1 includes season fixed effects, while Column 2 includes month fixed effects and Columns 3 includes week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.82: Crop Cultivator Households: Effect of Late Sunset on Individuals' Sleep (Hours) in Pre- vs. Post-Harvest Month, Controlling for Sunrise Time and Daylight Duration

	(1) Sleep β / SE	(2) Sleep β / SE	(3) Sleep β / SE
Sunset Time*Pre-Harvest	-0.35*	-0.27	-0.47**
	(0.18)	(0.21)	(0.22)
District FE	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes
Sunrise Time	No	Yes	No
Daylight Duration	No	No	Yes
Mean	8.42	8.42	8.42
Observations	10827	10827	10827
R^2	0.117	0.117	0.117

Notes: This table presents the effect of daily sunset time on time allocated to sleep before harvest compared to after harvest on weekdays for all individuals over the age of 6 from crop cultivator households in India. Each column represents a separate regression estimating Equation (11) on the outcome variable. The interaction term Sunset Time*Pre-Harvest captures the effect of an hour delay in daily sunset time for crop cultivator households in the pre-harvest month compared to the post-harvest month. Column 2 controls for sunrise time. Column 3 controls for daylight duration. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.83: Non-Cultivator Households: Effect of Late Sunset on Individuals' Sleep (Hours) in Pre- vs. Post-Harvest Month

	(1) Sleep β / SE	(2) Sleep β / SE	(3) Sleep β / SE
All			
Sunset Time (Hours)	-0.35***	-0.63**	-0.64**
	(0.11)	(0.28)	(0.29)
Sunset Time*Pre-Harvest	-0.06	0.21	0.09
	(0.10)	(0.20)	(0.19)
Mean	8.21	8.21	8.21
Observations	10363	10363	10363
R^2	0.069	0.072	0.081
Adults			
Sunset Time (Hours)	-0.38***	-0.78***	-0.70**
	(0.11)	(0.26)	(0.27)
Sunset Time*Pre-Harvest	-0.05	0.05	0.01
	(0.10)	(0.20)	(0.18)
Mean	7.96	7.96	7.96
Observations	7980	7980	7980
R^2	0.092	0.095	0.107
Children			
Sunset Time (Hours)	-0.33*	-0.46	-0.49
	(0.20)	(0.44)	(0.49)
Sunset Time*Pre-Harvest	-0.03	0.61**	0.28
	(0.15)	(0.30)	(0.30)
Mean	9.06	9.06	9.06
Observations	2383	2383	2383
R^2	0.120	0.131	0.156
District FE	Yes	Yes	Yes
Season FE	Yes	No	No
Month FE	No	Yes	No
Week-of-Year FE	No	No	Yes

Notes: This table presents the effect of daily sunset time on time allocated to sleep before harvest compared to after harvest on weekdays for non-crop cultivator households in India. Panel 'All' includes all individuals over the age of 6. Panel 'Adults' includes all individuals over the age of 16. Panel 'Children' includes all individuals between 6 and 16 years of age. Each panel-column combination represents a separate regression estimating Equation (11) on the outcome variable. The interaction term captures the effect of an hour delay in daily sunset time for crop cultivator households in the pre-harvest month compared to the post-harvest month. All regressions include district fixed effects. Column 1 includes season fixed effects, while Column 2 includes month fixed effects and Columns 3 includes week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.84: Non-Cultivator Households: Effect of Late Sunset on Adults' Bedtimes and Wake-up Times (Hours) in Pre- vs. Post-Harvest Month

	(1) Bedtime β / SE	(2) Bedtime β / SE	(3) Wake-up Time β / SE	(4) Wake-up Time β / SE
Sunset Time (Hours)	0.46**	0.43**	-0.17	-0.11
	(0.19)	(0.21)	(0.14)	(0.16)
Sunset Time*Pre-Harvest	-0.29**	-0.18	-0.11	-0.02
	(0.15)	(0.13)	(0.13)	(0.12)
District FE	Yes	Yes	Yes	Yes
Month FE	Yes	No	Yes	No
Week-of-Year FE	No	Yes	No	Yes
Mean	21.94	21.94	5.97	5.97
Observations	7878	7878	7891	7891
R^2	0.236	0.247	0.164	0.170

Notes: This table presents the effect of daily sunset time on bedtimes and wake-up times before harvest compared to after harvest on weekdays for non-crop cultivators over the age of 16 in India. Each column represents a separate regression estimating Equation (11) on the outcome variable. The interaction term captures the effect of an hour delay in daily sunset time for crop cultivator households in the pre-harvest month compared to the post-harvest month. All regressions include district fixed effects. Columns 1 and 3 include month fixed effects while Columns 2 and 4 include week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.85: Summary Statistics: Work Hours in Pre- vs. Post-Harvest Month

	Crop Cultivators		Non-Crop Cultivators		Agricultural Laborers	
	Pre	Post	Pre	Post	Pre	Post
All						
Any Work (Hours)	4.82	4.63	4.30	4.18	5.56	5.15
	(4.03)	(3.91)	(4.43)	(4.37)	(4.14)	(3.93)
Agricultural Work (Hours)	3.06	2.88	0.65	0.41	3.96	2.87
	(3.84)	(3.67)	(2.19)	(1.68)	(4.20)	(3.78)
Other Work (Hours)	1.76	1.75	3.65	3.77	1.60	2.28
	(2.65)	(2.70)	(4.33)	(4.33)	(2.89)	(3.36)
Observations	4986	5841	3901	6462	460	571
Adults						
Any Work (Hours)	5.78	5.46	5.29	5.15	6.76	6.16
	(3.80)	(3.73)	(4.40)	(4.36)	(3.61)	(3.63)
Agricultural Work (Hours)	3.78	3.51	0.79	0.51	4.89	3.65
	(3.95)	(3.78)	(2.39)	(1.85)	(4.15)	(3.93)
Other Work (Hours)	1.99	1.95	4.50	4.64	1.87	2.52
	(2.70)	(2.78)	(4.43)	(4.41)	(3.03)	(3.53)
Observations	3845	4615	3022	4958	357	429
Children						
Any Work (Hours)	1.59	1.50	0.89	0.98	1.43	2.08
	(2.97)	(2.81)	(2.39)	(2.47)	(3.09)	(3.10)
Agricultural Work (Hours)	0.63	0.51	0.17	0.11	0.74	0.53
	(2.02)	(1.80)	(1.14)	(0.86)	(2.38)	(1.90)
Other Work (Hours)	0.96	0.99	0.72	0.87	0.69	1.55
	(2.27)	(2.23)	(2.13)	(2.33)	(2.15)	(2.65)
Observations	1141	1226	879	1504	103	142

Notes: This table presents summary statistics on work hours for crop cultivator households, non-crop cultivator households, and agricultural laborer households disaggregated by the pre- and post-harvest month for children and adults on weekdays. Standard deviations in parentheses. Source: ITUS.

Table B.86: Agricultural Labor and Other Non-Cultivator Households: Effect of Late Sunset on Individuals' Sleep (Hours) in Pre- vs. Post-Harvest Month

	(1) Sleep β / SE	(2) Sleep β / SE	(3) Sleep β / SE
Agricultural Laborers			
Sunset Time (Hours)	-2.24***	-2.53*	-1.41
	(0.66)	(1.30)	(1.47)
Sunset Time*Pre-Harvest	0.32	0.16	0.10
	(0.76)	(0.74)	(0.914)
Mean	8.43	8.43	8.43
Observations	1031	1031	1031
R^2	0.212	0.223	0.263
All Non-Cultivator Households			
Sunset Time (Hours)	-0.28**	-0.58**	-0.60**
	(0.12)	(0.28)	(0.29)
Sunset Time*Pre-Harvest	-0.06	0.23	0.10
	(0.10)	(0.21)	(0.20)
Mean	8.19	8.19	8.19
Observations	9332	9332	9332
R^2	0.061	0.064	0.073
District FE	Yes	Yes	Yes
Season FE	Yes	No	No
Month FE	No	Yes	No
Week-of-Year FE	No	No	Yes

Notes: This table presents the effect of daily sunset time on time allocated to sleep before harvest compared to after harvest on weekdays for non-cultivator households in India. Panel 'Agricultural Laborers' includes all individuals over the age of 6 from agricultural laborer households. Panel 'Non-Cultivator Households' includes all individuals over the age of 6 from all non-cultivator households. Each panel-column combination represents a separate regression estimating Equation (11) on the outcome variable. The interaction term captures the effect of an hour delay in daily sunset time for crop cultivator households in the pre-harvest month compared to the post-harvest month. All regressions include district fixed effects. Column 1 includes season fixed effects, while Column 2 includes month fixed effects and Columns 3 includes week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.87: Crop Cultivator Households: Effect of Late Sunset on Individuals' Sleep (Hours) in Pre- vs. Post-Harvest Month for Richer vs. Poorer Households

	(1) Sleep β / SE	(2) Sleep β / SE	(3) Sleep β / SE
All			
Sunset Time (Hours)	-0.70***	-0.06	0.04
	(0.15)	(0.23)	(0.27)
Sunset Time*Pre-Harvest	-0.39***	-0.60***	-0.50***
	(0.12)	(0.20)	(0.19)
Sunset Time*HH Expenditure>50p*Pre-Harvest	0.16	0.19	0.21*
	(0.12)	(0.12)	(0.12)
Mean	8.42	8.42	8.42
Observations	10827	10827	10827
R^2	0.104	0.109	0.119
Adults			
Sunset Time (Hours)	-0.64***	0.01	0.20
	(0.16)	(0.26)	(0.29)
Sunset Time*Pre-Harvest	-0.39***	-0.60***	-0.57***
	(0.12)	(0.21)	(0.19)
Sunset Time*HH Expenditure>50p*Pre-Harvest	0.23*	0.23*	0.26**
	(0.13)	(0.13)	(0.13)
Mean	8.20	8.20	8.20
Observations	8460	8460	8460
R^2	0.145	0.151	0.162
Children			
Sunset Time (Hours)	-0.79***	-0.56	-0.61
	(0.20)	(0.36)	(0.43)
Sunset Time*Pre-Harvest	-0.34**	-0.49*	-0.35
	(0.17)	(0.29)	(0.27)
Sunset Time*HH Expenditure>50p*Pre-Harvest	0.12	0.18	0.20
	(0.18)	(0.18)	(0.17)
Mean	9.19	9.19	9.19
Observations	2367	2367	2367
R^2	0.134	0.144	0.160
District FE	Yes	Yes	Yes
Season FE	Yes	No	No
Month FE	No	Yes	No
Week-of-Year FE	No	No	Yes

Notes: This table presents the effect of daily sunset time on time allocated to sleep before harvest compared to after harvest on weekdays for richer vs. poorer crop cultivator households in India. Panel 'All' includes all individuals over the age of 6. Panel 'Adults' includes all individuals over the age of 16. Panel 'Children' includes all individuals between 6 and 16 years of age. Each panel-column combination represents a separate regression. The interaction term 'Sunset Time*Pre-Harvest' captures the effect of an hour delay in daily sunset time for crop cultivator households in the pre-harvest month compared to the post-harvest month. The interaction term 'Sunset Time*HH Expenditure>50p*Pre-Harvest' captures the effect of an hour delay in daily sunset time for richer crop cultivator households in the pre-harvest month compared to richer crop cultivator households in the post-harvest month. All regressions include district fixed effects. Column 1 includes season fixed effects, while Column 2 includes month fixed effects and Columns 3 includes week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

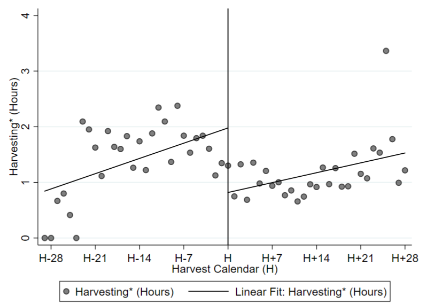
Pre- and Post-Harvest Period

The 6 states included in ITUS are Haryana, Madhya Pradesh, Gujarat, Orissa, Tamil Nadu, and Meghalaya. The major kharif crop across these states is rice. Rice harvest in Haryana ends in October. Therefore, October is denoted as the kharif pre-harvest month for Haryana, while November is denoted as the kharif post-harvest month. Similarly, the kharif pre-harvest (post-harvest) month for Madhya Pradesh, Gujarat, Orissa, Tamil Nadu, and Meghalaya is denoted as November (December), November (December), October (November), January (February), December (January), respectively.

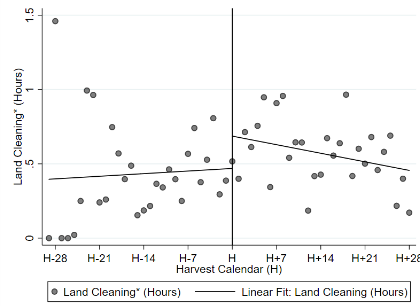
The major rabi crop for Haryana is wheat. Wheat harvest in Haryana ends in April. Therefore, April is denoted as the rabi pre-harvest month for Haryana, while May is denoted as the rabi post-harvest month. The major rabi crops for Madhya Pradesh, Gujarat, Orissa, Tamil Nadu, and Meghalaya are Wheat, Wheat, Pulses, Rice, and Rice, respectively. Correspondingly, the rabi pre-harvest (post-harvest) month is denoted as April (May), April (May), February (March), May (June), and June (July), respectively.

As a robustness check, I examine how crop cultivator households allocate time to various agricultural activities during the pre- and post-harvest months as defined above. Unfortunately, ITUS groups time allocated to harvest with time allocated to application of manure, fertilizer, pesticides and watering, preparing organic manure, threshing, picking, and winnowing. Similarly, time allocated to land cleaning is grouped with ploughing and land preparation, while sowing is grouped with planting, and transplanting. Nevertheless, as one might expect, I notice sharp decline in time allocated to 'harvesting' in the post-harvest month compared to the pre-harvest month, while time allocated to 'land cleaning' increases as farmers prepare for the next agricultural season (Figure B.34).

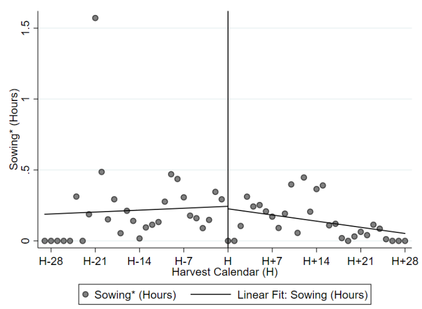
Figure B.34: Crop Cultivator Households: Relationship Between the Pre- and Post-Harvest Period and Time Allocated to Agricultural Activities



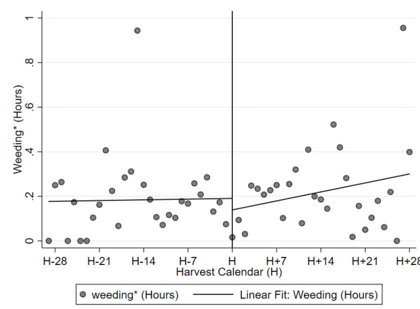
(a) Time Allocated to Harvesting*



(b) Time Allocated to Land Cleaning*



(c) Time Allocated to Sowing*



(d) Time Allocated to Weeding

Notes: This figure presents the relationship between the pre- and post-harvest period and time allocated to agricultural activities on weekdays. Unfortunately, ITUS groups time use as follows: 'Harvest' includes application of manure, fertilizer, pesticides and watering, preparing organic manure, harvesting, threshing, picking, and winnowing; 'Land Cleaning' includes ploughing, preparing land, and cleaning of land; 'Sowing' includes sowing, planting, and transplanting. H-28, H-21, H-14, and H-7 denote dates in the pre-harvest month (approximately) 28, 21, 14, and 7 days away from the harvest date H, respectively. While H+7, H+14, H+21, and H+28 denote dates in post-harvest month 7, 14, 21, and 28 (approximately) days after the harvest date H. Source: ITUS.

B.6 Appendix: India-Wide Human Capital Costs

Figure B.35: Spatial Variation in Annual Average Sunset Time in India

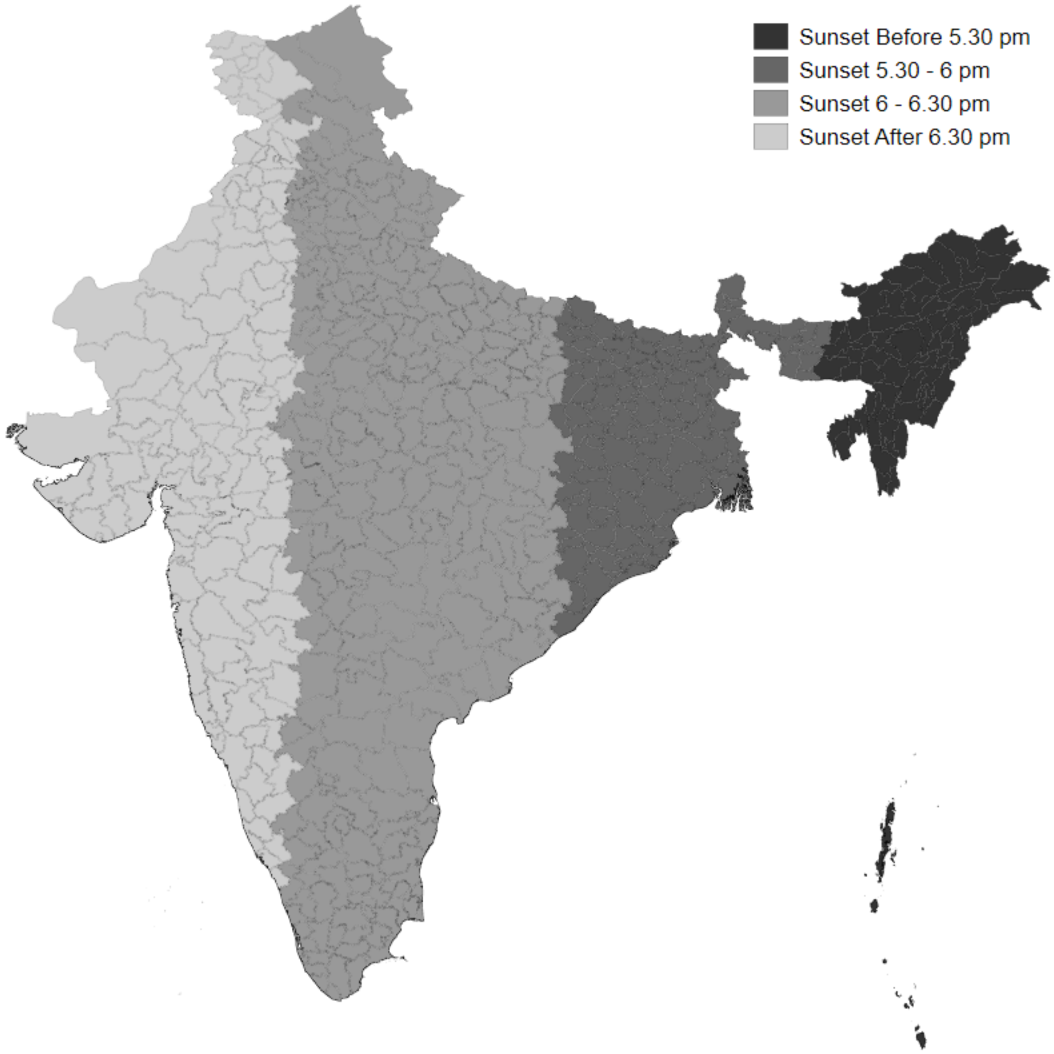
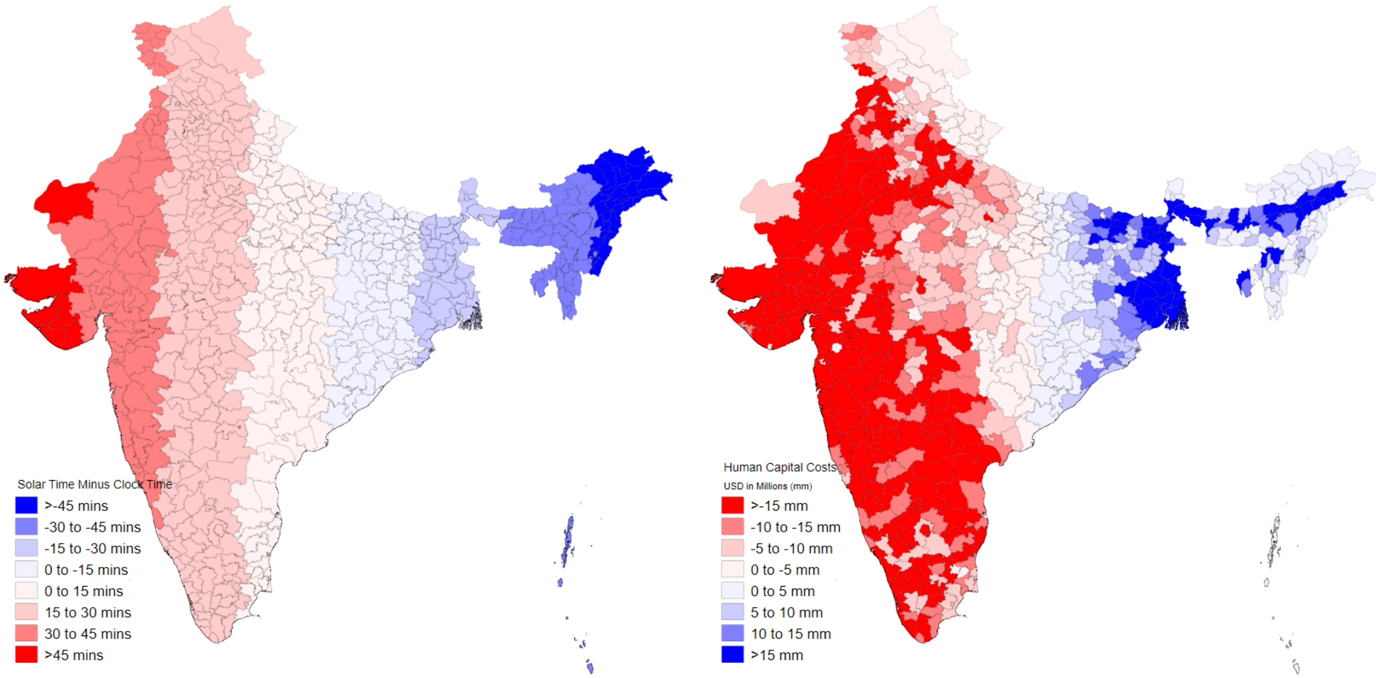


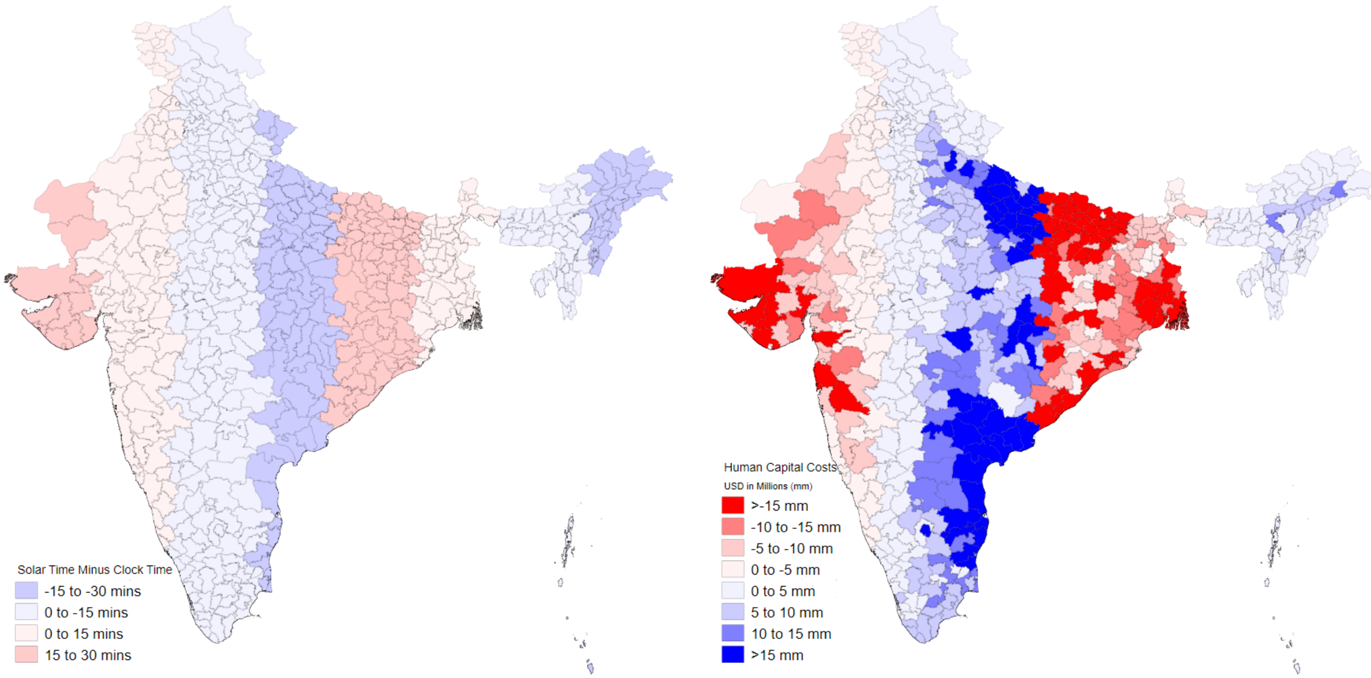
Figure B.36: Human Capital Costs Associated with Differences Between Mean Solar Time and Clock Time Across India Under the Existing Time Zone Policy – UTC+5.5



(a) Differences Between Mean Solar Time and Clock Time (b) Human Capital Costs Associated with Sunset Times

Notes: This figure presents the human capital costs associated with the existing time zone policy in India – UTC+5.5 – compared to the counterfactual of continuous time zones. Panel (a) present the differences between mean solar time and clock time associated with the existing time zone policy. Panel (b) presents human capital effects associated with sunset-induced reductions in sleep under the existing time zone policy. I compute the following equation for each district i: $HumanCapitalCosts_i = -8 * 312 * Population_i * (MeanSolarTime_i - IST)$, where INR 8 is the point estimate for the effect of an hour delay in sunset on adults' wages and 312 are the number of work days in a year. While $Population_i$ is the population of adults at the district level and $MeanSolarTime_i - IST$ is difference between the district-specific annual average sunset time and the annual average sunset time at 82.5° E, the central meridian of India.

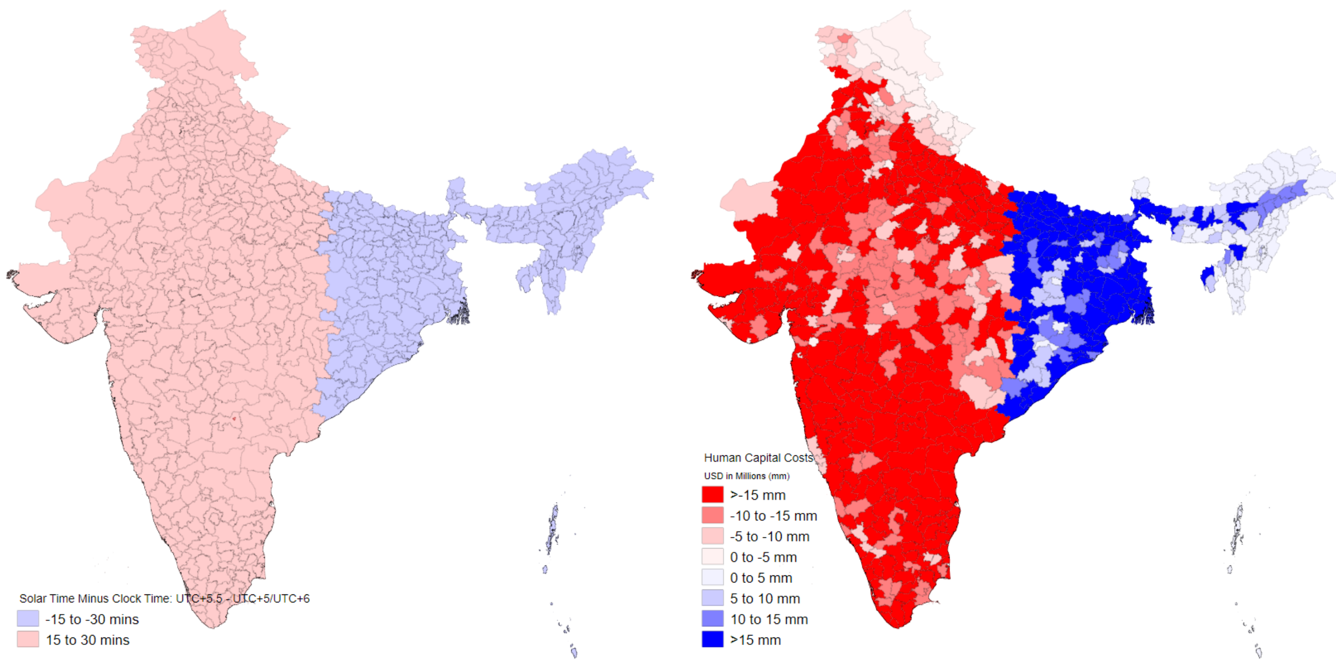
Figure B.37: Human Capital Costs Associated with Differences Between Mean Solar Time and Clock Time Across India Under a Hypothetical Time Zone Policy – UTC+5 in Western India and UTC+6 in Eastern India



(a) Differences Between Mean Solar Time and Clock Time (b) Human Capital Costs Associated with Sunset Times

Notes: This figure presents the human capital costs associated with a hypothetical time zone policy in India – UTC +5 in Western India and UTC+6 in Eastern India – compared to the counterfactual of continuous time zones. Panel (a) present the differences between mean solar time and clock time associated with the hypothetical time zone policy. Panel (b) presents human capital effects associated with sunset-induced reductions in sleep under the hypothetical time zone policy. I compute the following equation for each district i: $HumanCapitalCosts_i = -8 * 312 * Population_i * (MeanSolarTime_i - IST)$, where INR 8 is the point estimate for the effect of an hour delay in sunset on adults' wages and 312 are the number of work days in a year. While $Population_i$ is the population of adults at the district level and $MeanSolarTime_i - IST$ is difference between the district-specific annual average sunset time and the annual average sunset time at 75° E for western India and 90 ° E for eastern India, where western (eastern) India is defined as districts to the left (right) of 82.5° E.

Figure B.38: Human Capital Costs Associated with Differences in Sunset Time Between the Existing Time Zone Policy – UTC+5.5 and a Hypothetical Time Zone Policy – UTC+5 in Western India and UTC+6 in Eastern India



(a) Differences Between Mean Solar Time and Clock Time: UTC+5.5 - UTC+5/UTC+6

(b) Human Capital Costs Associated with Differences Between UTC+5.5 and UTC+5/UTC+6

Notes: This figure presents the human capital costs associated with the existing time zone policy – UTC+5.5 – compared to the counterfactual of a hypothetical time zone policy – UTC+5 in western India and UTC+6 in eastern India. Panel (a) present the differences between mean solar time and clock time across the two time zone policies. Panel (b) presents the differences in human capital effects associated with sunset-induced reductions in sleep across the two time zone policies. I compute the following equation for each district i: $HumanCapitalCosts_i = -8 * 312 * Population_i * (MeanSolarTime : UTC + 5.5_i - IST) - (MeanSolarTime : UTC + 5/UTC + 6 - UTC + 5/UTC + 6))$, where INR 8 is the point estimate for the effect of an hour delay in sunset on adults' wages and 312 are the number of days in a year. While $Population_i$ is the population of adults at the district level and $(MeanSolarTime : UTC + 5.5_i - IST) - (MeanSolarTime : UTC + 5/UTC + 6 - UTC + 5/UTC + 6)$ is difference between the district-specific differences in mean solar time and clock time according to the existing time zone policy – UTC+5.5 and a hypothetical time zone policy – UTC+5/UTC+6.

Table B.88: Effect of Late Sunset on School-Start Time Across the East-West Gradient

	(1) School Start Time β / SE
Sunset Time (Hours)	0.16
	(0.12)
Week-of-Year FE	Yes
Mean	9.20
Observations	8576
R^2	0.101

Notes: This table presents the effect of sunset time on school-start time across the east-west gradient. The regression includes week-of-year fixed effects. Standard errors are in parentheses, clustered at the week-of-year level. Source: ITUS.

B.7 Appendix: Policy Options

B.7.1 Later School Start Times

Recent evidence indicates that school start times are positively associated with test scores, presumably through the relationship between later school start times and children's sleep (86; 147; 195; 198; 414). Later school start times may allow children to compensate for later bedtimes associated with later sunset by waking up later and mitigate the negative effects of sleep deprivation on children's learning outcomes.

To test this hypothesis, I regress children's sleep on school start times. Using ITUS I generate an indicator for children who attend a school that starts its day after 8.30 am as a proxy for 'late school start time' (Table B.89).[12] Indeed, chil-

[12] The (16) recommends that schools delay the start of class to 8.30 am following medical research on children's sleep, school start times and learning.

dren attending schools with start times after 8.30 am are able to sleep an extra 30 minutes. Delaying the start of class to 8.30 am does not affect bedtimes, and the increase in sleep duration is solely driven by a delay in wake-up times.[13][14]

Next, I use YLS to examine if children attending schools that start after 8.30 am have better educational outcomes. The 2011 YLS School Survey collects Class 5 test scores for math, Hindi, science, social studies, Telugu and English for each school in the sample. I evaluate the interaction effects between later school start times and annual average sunset times and find suggestive evidence that delaying the start of class to 8.30 am attenuates the negative effect of later sunset on children's test scores (Tables B.92 and B.93). While the point estimates are underpowered across subjects (except science) they are positive. The coefficient capturing the interaction effects for science indicates that delaying the start of first period to 8.30 am attenuates the effects of an hour delay in annual average sunset time by over 60%. Such a large attenuation effect is precisely what one would expect as an hour delay in sunset decreases children's sleep by 30 minutes, all of which may be recouped by delaying the start of school to 8.30 am.[15]

Note that these results are only suggestive as the decision to attend schools with later start times may be endogenous to, amongst other factors, later sun-

[13]Moreover, I find that later school start times increase time allocated to study effort and decrease time allocated to leisure (Table B.90). These results are precisely what one would expect if sleep increases the marginal returns of an additional hour of study effort.

[14]Later school start times may also increase parents' sleep duration. In turn, if sleep is productivity-enhancing, time allocated to work effort may increase as well. On the other hand, if parents typically begin work before 8.30 am, then starting school after 8.30 am might reduce time allocated to work. Thus, the net effect on work time is ambiguous. I estimate this relationship empirically using parents' time use data. Later school start time increases parents' sleep and time allocated to work, while decreasing time spent on leisure (Table B.91). This result suggests that later school start times may have a positive effect on parents' productivity.

[15]Figures B.39 and B.40 present binned scatterplots of the reduced form relationship between school start time and sleep, and of the mitigative effect of later school start time on the sunset-test score relationship, respectively.

set. For instance, wealthier households may be aware of the negative effects of later sunset on children's educational output. Therefore, the modest effects on test scores in schools with later sunset times could be a proxy for underlying socioeconomic characteristics of children attending these schools. I evaluate such omitted variables by controlling for observable school-level features like type of school (public vs. private), medium of instruction, number of students and teachers etc. The addition of these controls explains meaningful variation in the outcomes of interest, but my point estimates only get larger (Tables B.94 and B.95). However, the interaction effects are still underpowered and should be interpreted with caution.

B.7.2 Social Protection Programs

Social protection programs can lead to large improvements in financial and psychological well-being among the poor (30; 32; 156; 192; 368; 369; 408). Specifically, a vast literature has shown that conditional cash transfer programs can have positive welfare effects among low-income households.[16]

Social protection programs like conditional cash transfer schemes may help the poor adjust their sleep schedules when the sun sets later, mitigating the effects on children's human capital production. This may happen in two ways. First, welfare programs may reduce children's sleep deficit when the sun sets later if families are able to afford financial (e.g., indoor beds, dark curtains) and psychological (e.g., attention) sleep-inducing goods. Second, if adults sleep

[16]For instance, (29) find that a conditional cash transfer program in Malawi reduced psychological distress among school-age girls. (7) and (164) show that conditional cash transfer programs attenuate the negative effects of environmental stressors on children's human capital accumulation. See (160) and (307) for an exhaustive review.

more due to access to social protection, welfare programs may attenuate the effects of later sunset on adults' wages and households' education expenditure.

To test this hypothesis, I examine a workfare program in India, the National Rural Employment Guarantee Act (NREGA), that was enacted in 2005, and guarantees 100 days of paid employment on rural infrastructure projects each year to every rural household. Workers can apply for work at any time, and if they are not given a job, they are eligible for unemployment compensation. Importantly, the program hires workers at a fixed daily wage set exogenously by every state government. Thus, income from NREGA may have an income-stabilizing effect as wages are less susceptible to sleep-induced productivity losses. In addition, NREGA may also increase local labor demand and wages.[17]

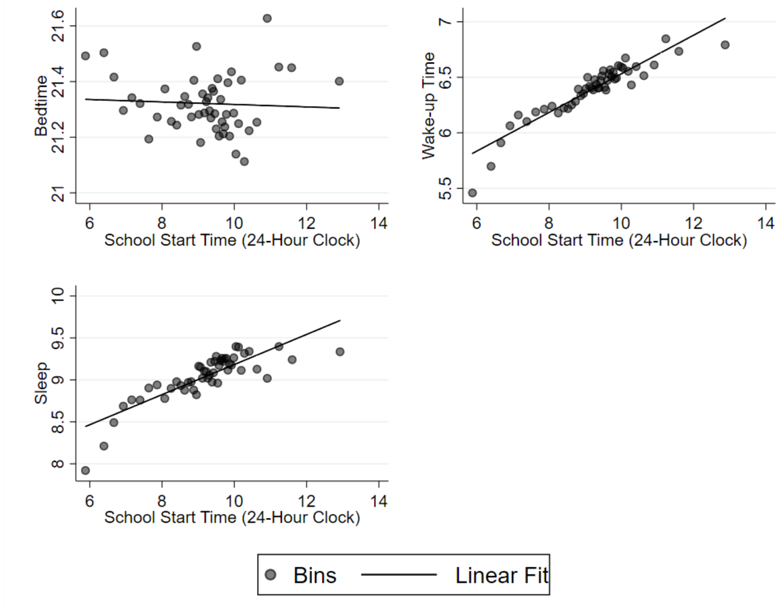
I use the individual level longitudinal panel from Andhra Pradesh, India, the 2002-2013 Young Lives Survey (YLS), and restrict the sample to rural households. I estimate intent-to-treat (ITT) effects, exploiting the staggered rollout of NREGA across Indian districts as a source of variation in access to a social protection program.[18] In 2006, the scheme was first rolled out in 200 districts. In 2007, another 130 districts were added while the program became available in the remaining 270 districts in 2008. I use individual-level math test score data and examine the coefficient of the interaction term between number of years of NREGA exposure and day-of-test (daily) sunset time at the district-test-date level. As expected, NREGA attenuates the effects of later sunset on test scores (Table B.96). Specifically, each additional year of exposure to NREGA mitigates

[17]Number of studies have shown that NREGA increased agricultural wages by roughly 5% (27; 52; 211).

[18]NREGA rollout wasn't random as poorer districts experienced rollout first. Therefore, the level effect of NREGA on children's outcomes is likely biased.

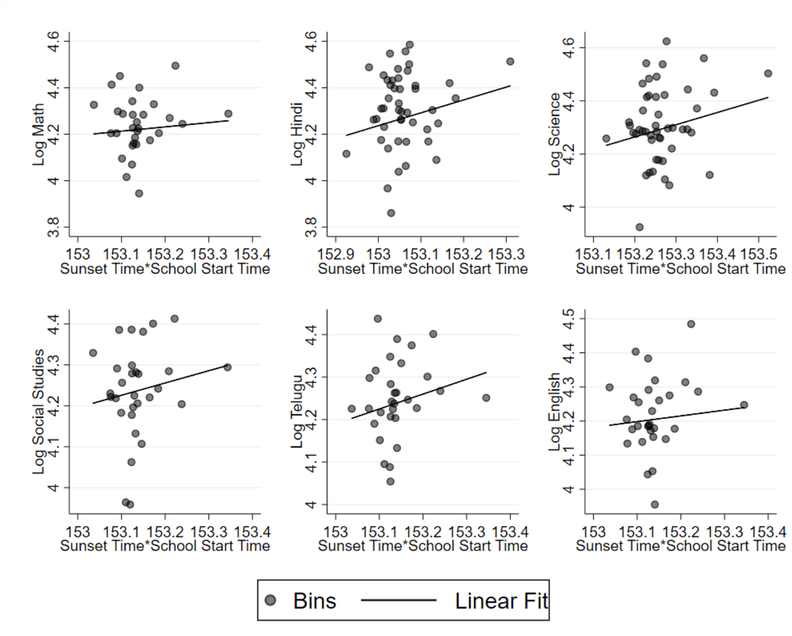
the effect of short-term sunset-induced sleep deficits on math test scores by roughly 5%.

Figure B.39: Effect of School Start Time on Bedtime, Wake-up Time, and Sleep



Notes: This figure presents binned scatterplots for the relationship between school start time and sleep schedules for children between 6 and 16 years of age. Residuals for both children's sleep and school start time are plotted after absorbing district and week-of-year fixed effects. Source: ITUS.

Figure B.40: Do Later School Start Times Attenuate the Sunset-Test Score Relationship?



Notes: This figure presents binned scatterplots of the mitigative effects of later school start times on the sunset-test score relationship. Controls include school start time, annual average sunset time and school shift (morning or evening). Source: YLS.

Table B.89: Effect of School Start Times on Bedtime and Wakeup Time (Hours)

	(1) Bedtime β / SE	(2) Wake-up Time β / SE	(3) Sleep β / SE
School Start>8.30am	-0.01	0.50***	0.51***
	(0.03)	(0.03)	(0.05)
District FE	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes
Mean	21.32	6.39	9.04
Observations	8525	8547	8576
R^2	0.192	0.337	0.152

Notes: This table presents the effect of school start time on bedtime and wakeup time for children between 6 and 16 years of age on weekdays. Each column represents a separate regression. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.90: Effect of School Start Times on Children's Time Use (Hours)

	(1) Study β / SE	(2) Leisure β / SE	(3) Work β / SE
School Start>8.30am	0.34***	-0.75***	-0.03
	(0.06)	(0.08)	(0.03)
District FE	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes
Mean	2.08	6.39	0.42
Observations	8576	8576	8576
R^2	0.234	0.276	0.134

Notes: This table presents the effect of school start time on study, leisure and work for children between 6 and 16 years of age on weekdays. Each column represents a separate regression. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.91: Effect of School Start Times on Parent's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE	(5) HH Chores β / SE	(6) Time With Kids β / SE
School Start>8.30am	0.12***	-0.01	-0.29***	0.24***	-0.06	0.01
	(0.03)	(0.02)	(0.08)	(0.08)	(0.04)	(0.02)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean	8.04	0.15	6.84	5.39	2.88	0.44
Observations	14428	14428	14428	14428	14428	14428
R^2	0.097	0.014	0.050	0.029	0.022	0.028

Notes: This table presents the effect of school start time on time allocated to sleep, study, leisure, work, home production and time spent with children by individuals over 16 years of age on weekdays in India. Each column represents a separate regression. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table B.92: Math, Hindi and Science: Do Later School Start Times Attenuate the Sunset-Test Score Relationship?

	(1) Log Math β / SE	(2) Log Hindi β / SE	(3) Log Science β / SE
Annual Average Sunset Time (Hours)	-0.24	-0.52**	-0.62***
	(0.23)	(0.24)	(0.20)
Annual Average Sunset Time (Hours)*School Start>8.30am	0.11	0.28	0.42*
	(0.25)	(0.26)	(0.23)
Observations	225	106	114
R^2	0.027	0.115	0.113

Notes: This table presents the effect of annual average sunset time on the average scores for children in Class 5 at the school level as well as the mitigative effects of later school start times on the sunset-test score relationship. Each column represents a separate regression. All regressions include controls for school shift (morning or evening). Heteroskedasticity robust standard errors are in parentheses. Source: YLS.

Table B.93: Social Studies, Telugu and English: Do Later School Start Times Attenuate the Sunset-Test Score Relationship?

	(1) Log Social Studies β / SE	(2) Log Telugu β / SE	(3) Log English β / SE
Annual Average Sunset Time (Hours)	-0.26	-0.25	-0.19
	(0.18)	(0.18)	(0.21)
Annual Average Sunset Time (Hours)*School Start>8.30am	0.12	0.08	0.02
	(0.21)	(0.21)	(0.24)
Observations	221	225	225
R^2	0.025	0.032	0.034

Notes: This table presents the effect of annual average sunset time on the average scores for children in Class 5 at the school level as well as the mitigative effects of later school start times on the sunset-test score relationship. Each column represents a separate regression. All regressions include controls for school shift (morning or evening). Heteroskedasticity robust standard errors are in parentheses. Source: YLS.

Table B.94: Math, Hindi and Science (Other Controls): Do Later School Start Times Attenuate the Sunset-Test Score Relationship?

	(1) Log Math β / SE	(2) Log Hindi β / SE	(3) Log Science β / SE
Annual Average Sunset Time (Hours)	-0.70***	-0.99***	-0.79***
	(0.22)	(0.35)	(0.27)
Annual Average Sunset Time (Hours)*School Start>8.30am	0.30	0.44	0.36
	(0.25)	(0.35)	(0.28)
Other Controls	Yes	Yes	Yes
Observations	199	102	107
R^2	0.358	0.366	0.440

Notes: This table presents the effect of annual average sunset time on the average scores for children in Class 5 at the school level as well as the mitigative effects of later school start times on the sunset-test score relationship. Each column represents a separate regression. All regressions include controls for latitude, school shift (morning or evening), type of school (public vs. private), medium of instruction, number of students, number of teachers, school location, if school receives textbooks from government, if the school teaches English, if the school offers boarding facilities, highest grade taught at school, medium of instruction, if the school offers pre-primary education, if the school is a branch school. Heteroskedasticity robust standard errors are in parentheses. Source: YLS.

Table B.95: Social Studies, Telugu and English (Other Controls): Do Later School Start Times Attenuate the Sunset-Test Score Relationship?

	(1) Log Social Studies β / SE	(2) Log Telugu β / SE	(3) Log English β / SE
Annual Average Sunset Time (Hours)	-0.53**	-0.49**	-0.38
	(0.22)	(0.21)	(0.25)
Annual Average Sunset Time (Hours)*School Start>8.30am	0.16	0.23	0.19
	(0.24)	(0.23)	(0.26)
Other Controls	Yes	Yes	Yes
Observations	196	199	199
R^2	0.352	0.292	0.409

Notes: This table presents the effect of annual average sunset time on the average scores for children in Class 5 at the school level as well as the mitigative effects of later school start times on the sunset-test score relationship. Each column represents a separate regression. All regressions include controls for latitude, school shift (morning or evening), type of school (public vs. private), medium of instruction, number of students, number of teachers, school location, if school receives textbooks from government, if the school teaches English, if the school offers boarding facilities, highest grade taught at school, medium of instruction, if the school offers pre-primary education, if the school is a branch school. Heteroskedasticity robust standard errors are in parentheses. Source: YLS.

Table B.96: Does NREGA Attenuate the Sunset-Test Score Relationship?

	(1) Math (SD) β / SE	(2) Math (SD) β / SE
Daily Sunset Time (Hours)	-0.728**	-0.682*
	(0.370)	(0.385)
Daily Sunset Time (Hours)*NREGA (# of Years)	0.022*	0.049***
	(0.012)	(0.013)
NREGA (# of Years)	0.483*	-0.020
	(0.252)	(0.276)
Age Dummies	Yes	Yes
Week-of-Year FE	Yes	Yes
Child FE	Yes	Yes
Weather Controls	No	Yes
Observations	5612	5612
R^2	0.777	0.781

Notes: This table presents the impact of short-run exposure to later sunsets on math test scores and the mitigative effects of NREGA on the sunset-test score relationship. 'NREGA (# of Years)' denotes the number of years the district had access to NREGA in the year the math test was conducted. All regressions include age, week-of-year, and child fixed effects. Column 2 also include day-of-week fixed effects as well as controls for weather. Standard errors are in parentheses, clustered at the child level. Source: YLS.

Appendix C

Chapter 3 of appendix

C.1 Climate Change Projections

To estimate the predicted impact of future climate change, we use climate projection data from a business-as-usual scenario from the National Center for Atmospheric Research's (NCAR) Community Climate System Model 4 (CCSM4) Global Circulation Model (283). Details of the model are described in (167).[1] An earlier version of this model was used in the fourth IPCC Assessment Report (213).

CCSM4 model output predictions are available for several Representative Concentration Pathways (RCPs), each of which is a greenhouse gas concentration (not emissions) trajectory adopted by the IPCC for its fifth Assessment Report. We focus on RCP 8.5, which is a high-concentration pathway or "business-

[1]Information about the model and other related models can also be found at http://www.cesm.ucar.edu/experiments/.

as-usual" scenario that is appropriate to consider when judging future impacts in the absence of policies to restrict greenhouse gas emissions.

We accessed daily average temperature predictions for grid points spanning India for the CCSM4 model for the years 2075-2099.[2] The model output is based on a single run of the model and is available for 1 degree by 1.25 degree latitude–longitude grid. To convert from the gridded projection data to our districts, we calculate the inverse-distance weighted average among all grid points within 100 km of each district centroid.

To compute the impact of projected climate change on future test scores, we calculated the average number of days in each temperature bin under the current climate for our sample (2004-2014) and compared that to the average number of of days in each temperature bin under the projected climate for end of century (2075-2099). Panel (a) of Figure C.1 shows these two bin distributions. We then calculated the change in number of days for each bin and multiplied that by the appropriate coefficient from our temperature–test score regression to estimate the impact of projected climate change on test scores. Panel (c) of Figure C.1 shows these impacts. As can be seen from the figure, for bins 6, 7, and 8 there will be small gains for test scores, as the coefficients for these bins are negative, and there will be reductions in the number of days in these bins under climate change. However, these is more than offset by the large increase in number of bin 10 days, which leads to an overall net decrease in scores.

Panel (e) presents the bin-by-bin impacts on test scores, but weights the calculations by the rural population in each district (instead of weighting each district equally). Panels (b), (d), and (f), present results analogous to panels (a), (c),

[2]The CCSM4 output data can be accessed from https://www.earthsystemgrid.org.

and (e), but focus on growing season temperature bins. Focusing on panel (d), which gives growing season impacts with equally weighted districts, we find an he overall impact that we find on test scores is a reduction of 0.04 standard deviations for math and 0.03 standard deviations for reading, for each year that a child is in school.

C.2 Converting Test Score Gains into Schooling Years and Wages

In order to convert these reductions in test score standard deviations to more concrete measures, we follow the methodology and parameter estimates from (150). These estimates are based on the World Bank's STEP Skills Measurement Program, which is a test designed to test proficiency in literacy with respect to word meaning, sentence processing and basic passage comprehension, in the language of the resident country (422).[3] (150) find a one standard deviation gain in literacy skill is associated with between 4.7 and 6.8 additional years of schooling. In other words, it takes about 4.7 to 6.8 years of schooling to increase literacy skills by one standard deviation. Using this metric, our result that reading scores decrease by 0.06 standard deviations if a child experiences 10 hot days during the growing season in the previous year, means that this is equivalent to reducing the effective years of schooling the child has received by 0.35 years [5.75*0.06 SD] (using 5.75 years of equivalent schooling as the conversion factor,

[3] Like the World Bank's STEP Skills Measurement Program, the ASER reading test is designed to capture basic literacy skills (35). Therefore, in this exercise, we focus only on the impacts of extra hot days on reading test scores. In addition, since our growing season specification is our preferred specification, we focus specifically on the impact of additional hot days during the growing season.

which is the midpoint of the range of the estimates of 4.7 to 6.8).

We can also convert this reduction of equivalent schooling into a wage loss, using the methodology and assumptions in (150). Assume that students enter the labor market at age 20 and work for 40 years. Furthermore, use a social discount rate of 3%, as is common in the literature in public finance (64; 184; 188). Following (150) and (25), we use the estimate that a one standard deviation increase in literacy skills is associated with a 51% increase in wages. Hence, 10 additional hot days will lead to a 3% decrease in wages [0.51*0.06 SD].

Turning to our CCSM projections, we can do some similar calculations. Here, we examine how the distribution of daily temperatures in the growing season will look in India by the end of the century (under a business-as-usual emissions scenario), and we estimate the impact that this will have on a child's test scores, assuming that the impacts will accrue over all 12 years of a child's schooling (ages 5 to 16). Using this approach, we find that the higher temperatures will lead to a reduction of the equivalent years of schooling of -2.07 years (-0.03 SD * 5.75 * 12).

In addition, we can use the methodology and assumptions in (150), to convert this reduction of equivalent years of schooling into a wage impact and into a net present value. Using the estimates from (150) and (25), we find that the reduction in schooling due to higher temperatures at the end of the century, accrued over a student's 12 years of schooling, will lead to a 18.36% decrease in wages [-0.03 SD *12*0.51]. We further convert this into a net present value; in 2015 the GNI per capita in India (2015 USD PPP) was $6,020, with a 0.29 labor share of income (422), demonstrating that the average labor income of a worker was $1,769. Hence a 18.36% decrease in wages is worth $325/year. Over a 40-year work life, this fixed additional income has a present value of roughly \$7,500, if discounted at 3 percent.

C.3 Other Alternative Explanations

C.3.1 School Closures and Teacher Attendance

Quality of instruction is a central component of virtually all proposals to raise school quality (186). Teaching quality has been linked to student test scores, as well as to later-life outcomes (96; 97). High temperatures can increase the cost of effort required to attend school and lead to teacher absenteeism, and consequently impact human capital production.[4] Furthermore, it is possible that schools are closed in response to very hot days (9), thereby affecting learning and test performance. We find two pieces of evidence that are inconsistent with such a hypothesis. First, if heat-induced school closures or teacher absenteeism were driving our results, we would see the effects on performance of only hot days during the school year (Figure C.12). The near-identical effects of heat during the school and non-school parts of the year suggest that teacher attendance or school closures are not the sole mechanism driving our results. However, we cannot fully rule out the possibility that, in addition to agricultural mechanisms, teacher attendance and school closures might be contributing to part of the relationship that we find.

[4]This problem is notable in India. Using unannounced visits to measure attendance, a nationally representative survey found that 24% of teachers in India were absent during school hours (93). (141) use a randomized control trial in India that incentivized teachers' attendance and find that teacher absenteeism fell and test scores of children in the treatment group increased.

Second, we explicitly test the effect of hot days on teacher attendance using the teacher attendance module of the ASER data. We find that hot days in the previous year and the current year do not affect teacher attendance (Table C.12). Thus, we fail to find evidence that teacher attendance is the key factor linking hotter days to reduced test score performance. Again however, we cannot fully rule out this possibility.

C.3.2 Disease Prevalence

An alternative explanation to the temperature-test score relationship could be through increased disease incidence (313). To the extent that health affects performance, temperature could affect test scores through an increase in the population of disease-carrying pathogens, particularly those carrying malaria. Some of the rainiest months of the year are during the growing season, and since rainfall and humidity favor *Anopheles* growth, our growing season versus non-growing season estimates cannot rule out the malaria channel. We consider this disease-prevalence mechanism to be distinct from the disease susceptibility effects that may occur via the agricultural income channel (the latter occurring when reduced household income affects health status, including disease vulnerability, through channels such as nutrition). Although we control for rainfall and humidity in our main specification, and our results remain robust to the inclusion of state-by-year fixed effects, insofar as higher temperatures independently increase the incidence of disease variably within a given state-year, our results might be a function of such a mechanism.

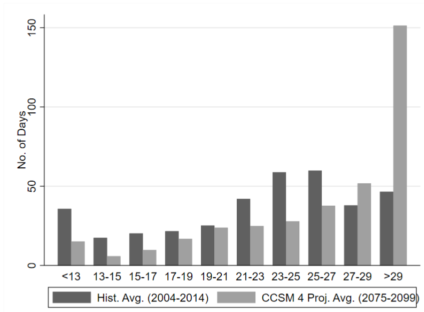
However, because of the life cycle of disease pathogens we would expect more recent higher temperatures to have a larger effect on health, and therefore performance, than similar days in the previous calendar year. Malaria, for example, is transferred through the *Anopheles* mosquito, which typically has a life cycle of two to four weeks, so if malarial incidence were driving our result, we should see an impact of hot days in the current year as well. In Table 4.2, we show that temperature in the current year has no effect on test score performance.[5] Prima facie, this suggests that the disease ecology of malaria is not driving the temperature-test score relationship. Additionally, we follow (356) and exploit the geographic differences in prevalence of malaria across India and show that the effects of temperature don't vary with malaria prevalence. In Figure C.13 we compare all other states against these malaria-prone states. Importantly, we show that during the growing season, there is no meaningful difference in the effects of temperature on test scores across malaria-prone and other states, suggesting that malaria is unlikely to be the driving factor behind the negative relationship between higher temperatures and test scores.[6]

[5]Hotter days in the current year have been associated with higher prevalence of malaria (313).

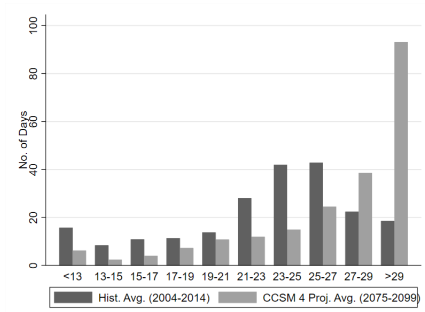
[6]The malaria-prone states are Chhattisgarh, Jharkhand, Orissa, Karnataka, and West Bengal.

C.4 Figures

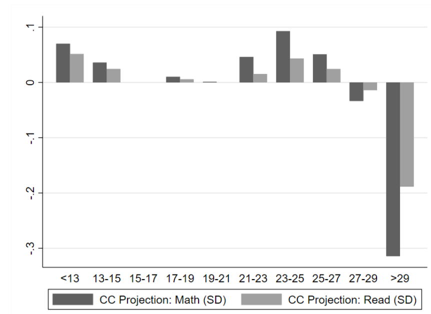
Figure C.1: CCSM Projections



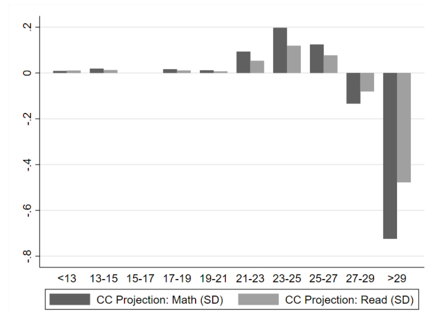
(a) Number of Hot Days



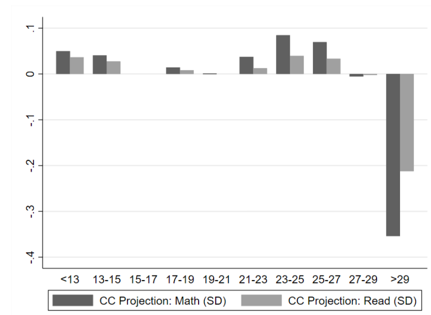
(b) Number of Hot Days in Growing Season



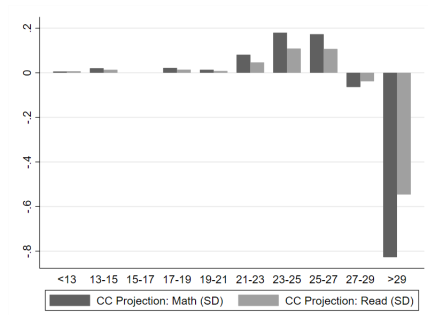
(c) Number of Hot Days*Effect of Hot Days



(d) Number of Hot Days in Growing Season*Effect of Hot Days

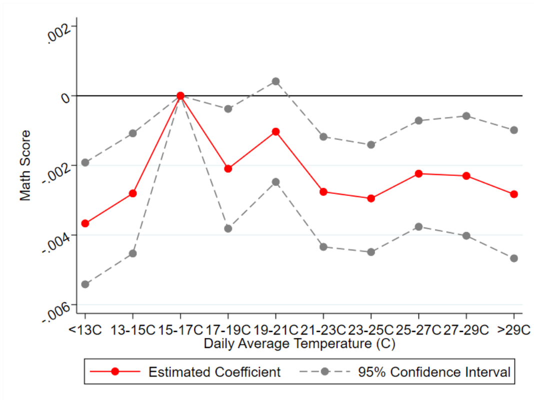


(e) Number of Hot Days*Effect of Hot Days (Weighted by Rural Population)

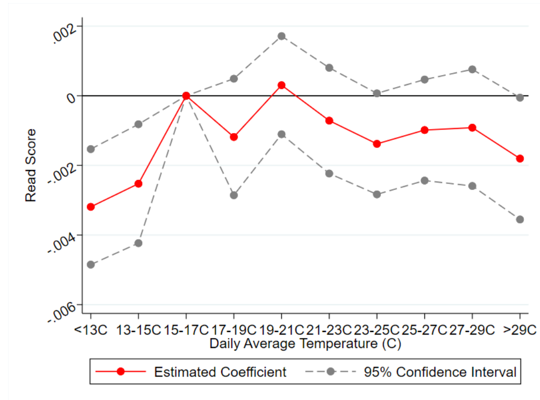


(f) Number of Hot Days in Growing Season*Effect of Hot Days (Weighted by Rural Population)

Figure C.2: Previous Year Temperature and Test Scores (ASER)



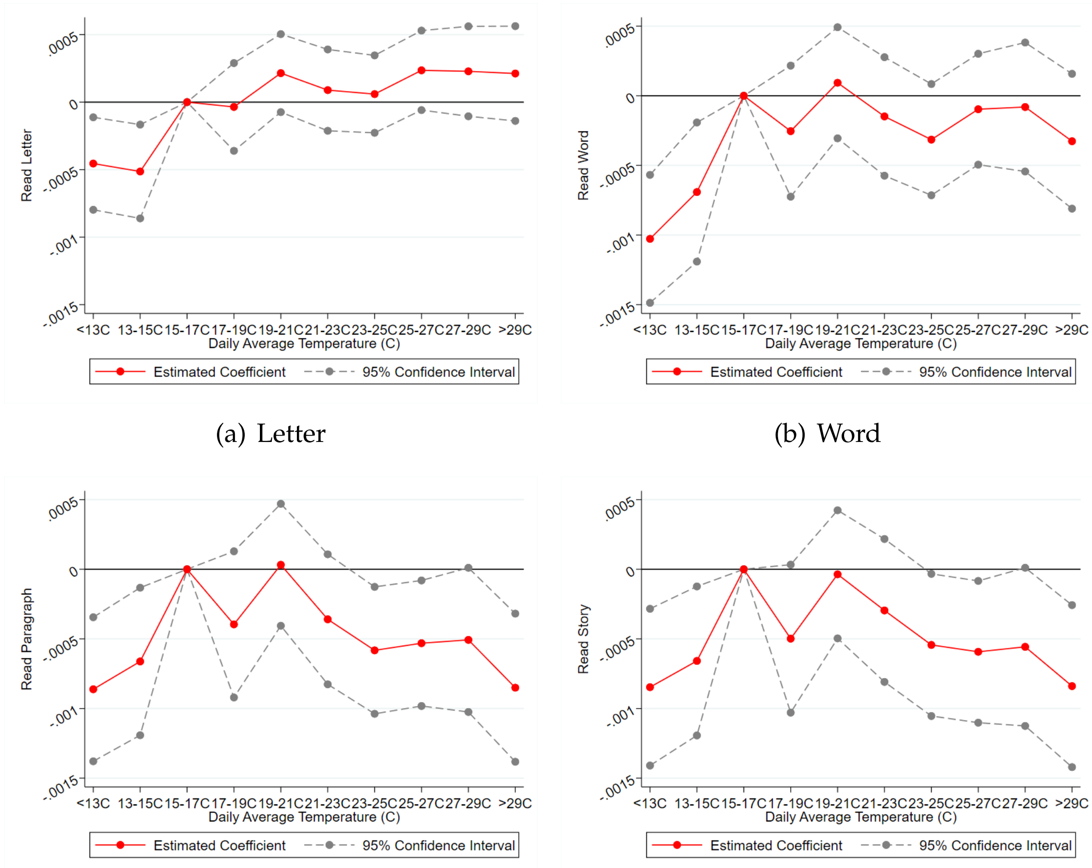
(a) Math Scores (ASER)



(b) Reading Scores (ASER)

Notes: Panels (a) and (b) show the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 4.3) on current year raw math and reading scores using the ASER data set. The effect of days between 15°C-17°C is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C. The regressions include district, year and age fixed effects. We control flexibly for precipitation and humidity. Standard errors are clustered at the district level.

Figure C.3: Previous Year Temperature and Reading Ability (ASER)



(a) Letter

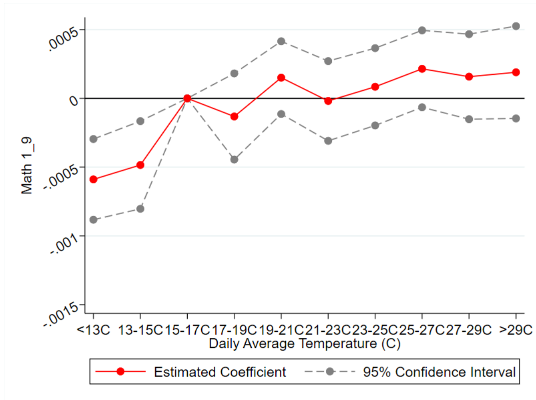
(b) Word

(c) Paragraph

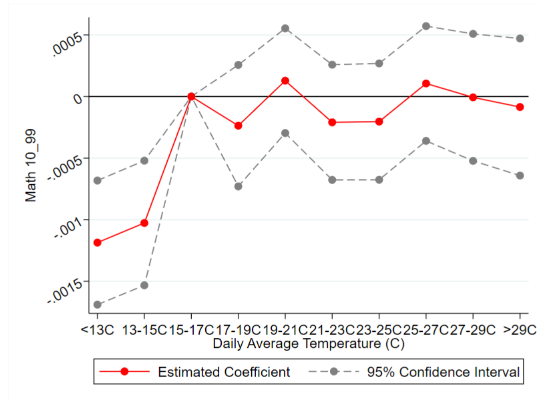
(d) Story

Notes: Panels (a), (b), (c) and (d) show the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 4.3) on reading ability using the ASER data set. The effect of days between 15°C-17°C is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C. The regressions include district, year and age fixed effects. We control flexibly for precipitation and humidity. Standard errors are clustered at the district level.

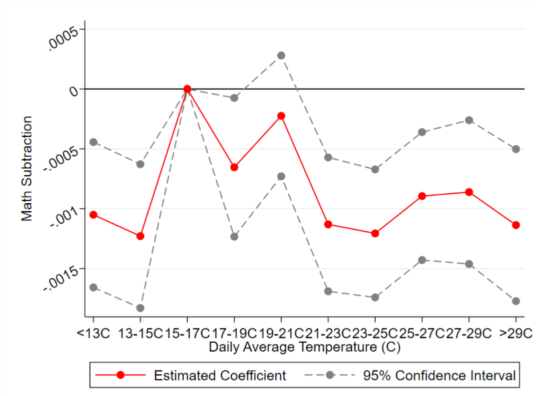
Figure C.4: Previous Year Temperature and Math Ability (ASER)



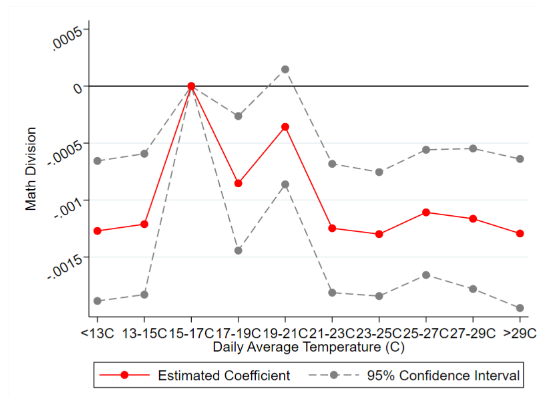
(a) Single Digit Number Recognition



(b) Double Digit Number Recognition



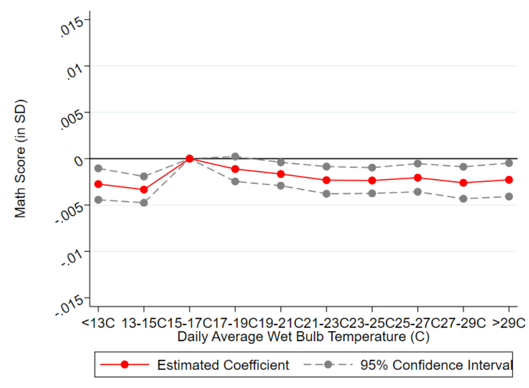
(c) Subtraction



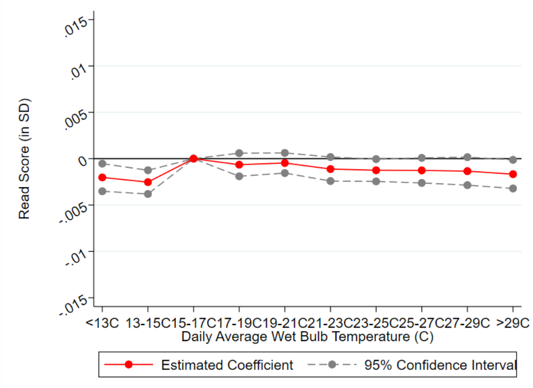
(d) Division

Notes: Panels (a), (b), (c) and (d) show the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 4.3) on current year math ability using the ASER data set. The effect of days between 15°C-17°C is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C. The regressions include district, year and age fixed effects. We control flexibly for precipitation and humidity. Standard errors are clustered at the district level.

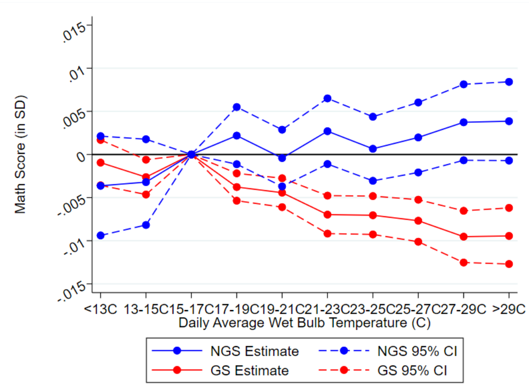
Figure C.5: Wet Bulb Global Temperatures (WBGT): Previous Year Temperature and Test Scores (ASER)



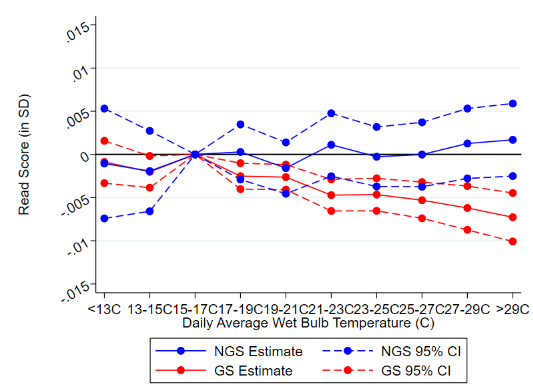
(a) Math Scores



(b) Reading Scores



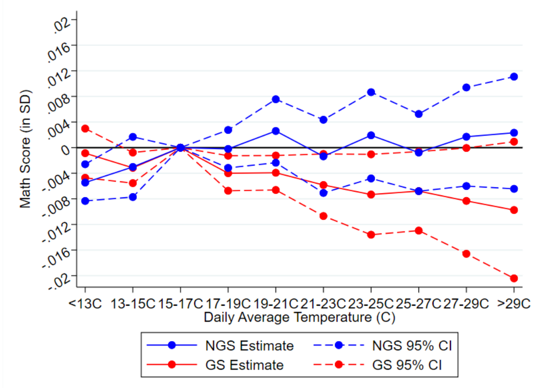
(c) Math Scores



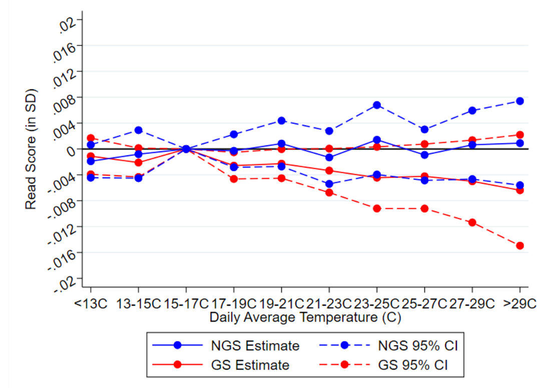
(d) Reading Scores

Notes: Panel (a) and (b) show the effect of longer-run WBGT temperature (defined as number of days in the previous calendar year—see Figure 4.3) on current year math and reading performance. In panel (c) and (d) the figure shows the effect of longer-run WBGT temperature (defined as number of days in the previous calendar year—see Figure 4.3) on current year math and reading performance divided amongst the growing season (June—Dec) and the non-growing season (March—May). In all panels, the effect of days between 15°C-17°C is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C. The regressions include district, year and age fixed effects. We control flexibly for precipitation and humidity. Standard errors are clustered at district level. GS: Growing Season; NGS: Non-Growing Season.

Figure C.6: Standard Errors Clustered at the State Level: Previous Year Temperature and Test Scores (ASER)



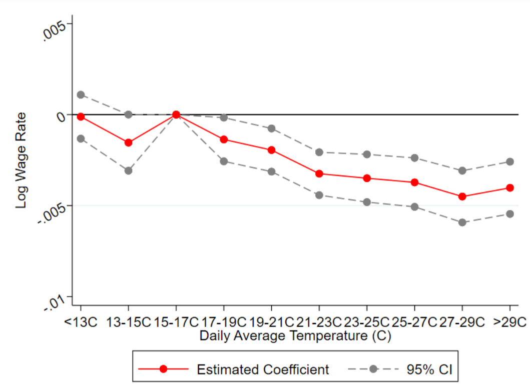
(a) Math Scores



(b) Reading Scores

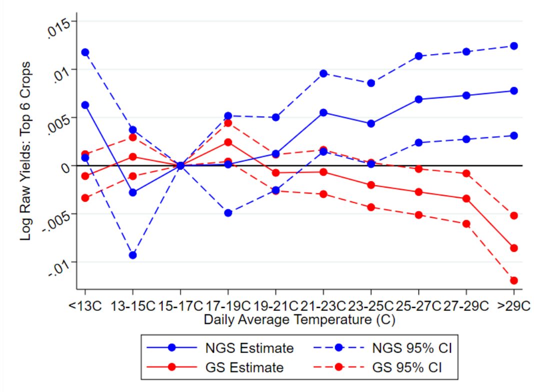
Notes: Panel (a) and (b) show the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 4.3) on current year math and reading performance divided amongst the growing season (June—Dec) and the non-growing season (March—May). In all panels, the effect of days between 15°C-17°C is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C. The regressions include district, year and age fixed effects. We control flexibly for precipitation and humidity. Standard errors are clustered at state level. GS: Growing Season; NGS: Non-Growing Season.

Figure C.7: Previous Year Temperature and Agricultural Wages

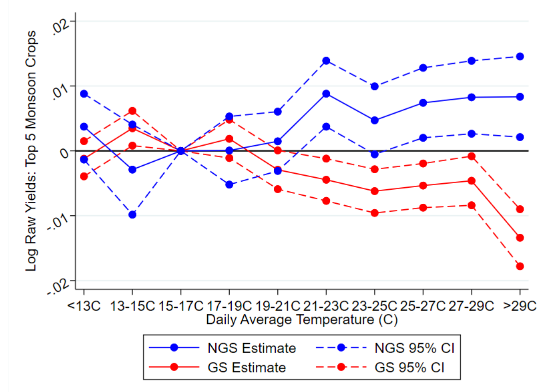


Notes: This figure shows the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 4.3) on previous year agricultural wages from 1980—2014. In all panels, the effect of days between 15°C-17°C is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C. The regressions include district and year fixed effects. We control flexibly for precipitation. Standard errors are clustered at district level.

Figure C.8: Growing Season v. Non-Growing Season: Previous Year Temperature and Raw Agricultural Yields



(a) Top 6 Crops



(b) Top 5 Monsoon Crops

Notes: Panel (a) and (b) show the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 4.3) on previous year raw agricultural yields from 1979—2014 divided amongst the growing season (June—Dec) and the non-growing season (March—May). In all panels, the effect of days between 15°C-17°C is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C. The regressions include district and year fixed effects. We control flexibly for precipitation. Standard errors are clustered at district level. GS: Growing Season; NGS: Non-Growing Season.

Figure C.9: Historical (Average) Take-Up of Heat Resistant Crops by District

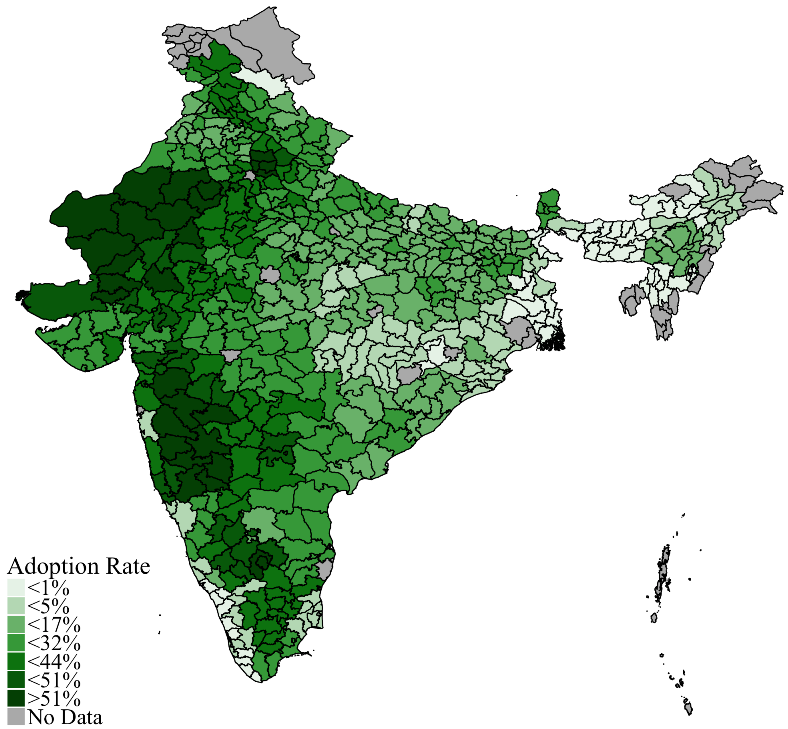
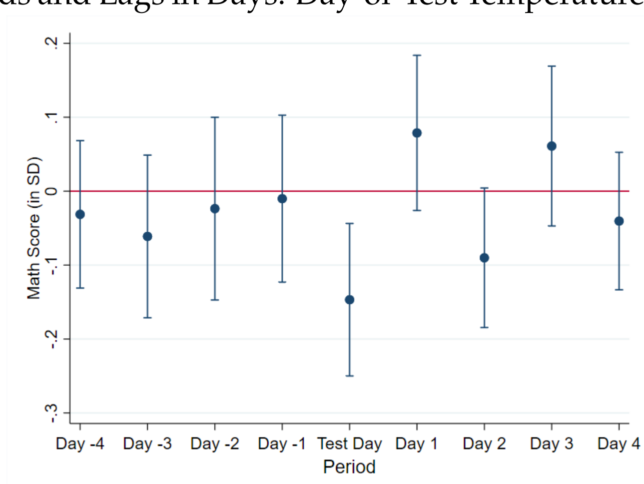
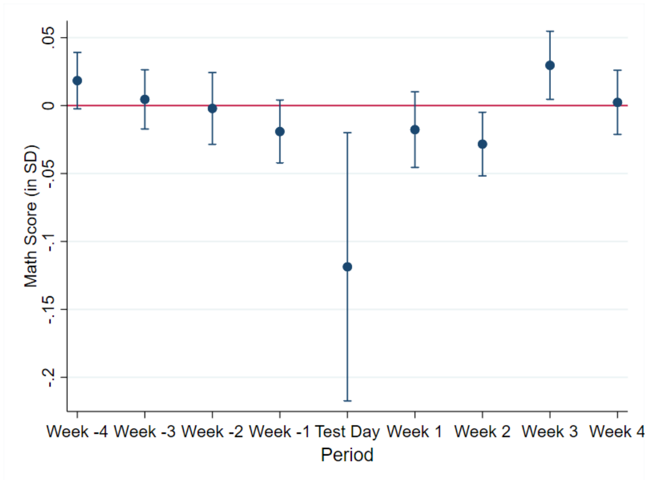


Figure C.10: Leads and Lags in Days: Day-of-Test Temperature and Math Scores



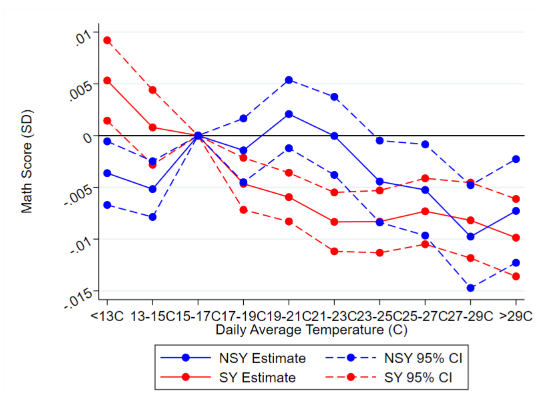
Notes: The figure presents the impact of short-run temperature from four weeks before test day to four weeks after the test. Temperature is captured as 1 if temperature is > 23 on the day of the test for "Test Day", 0 otherwise. Includes individual, day of week, month, and survey round fixed effects. We control for precipitation and humidity in all periods. Standard errors are clustered at the district-week level. 95% confidence intervals are presented in the figure.

Figure C.11: Leads and Lags in Weeks: Day-of-Test Temperature and Math Scores

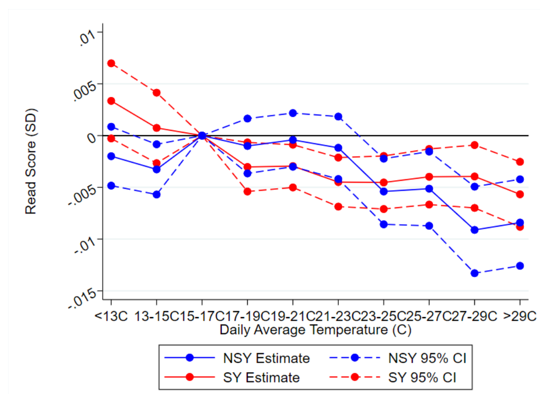


Notes: The figure presents the impact of short-run temperature from four weeks before test day to four weeks after the test. Temperature is captured as the number of days when the temperature is >23°C during a week for "*No.* Week", and if temperature is > 23 on the day of the test for "Test Day". Includes individual, day of week, month, and survey round fixed effects. We control for precipitation and humidity in all periods. Standard errors are clustered at the district-week level. 95% confidence intervals are presented in the figure.

Figure C.12: School Year v. Non-School Year: Previous Year Temperature and Test Scores (ASER)



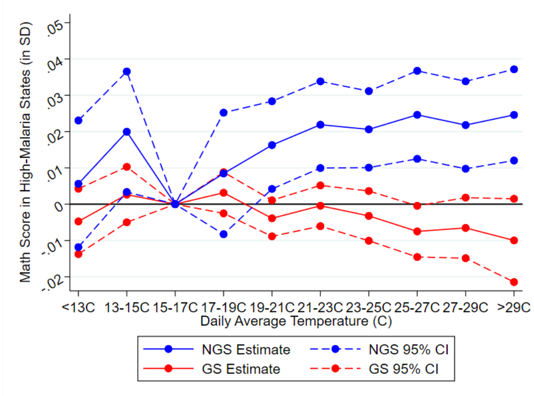
(a) Math Scores



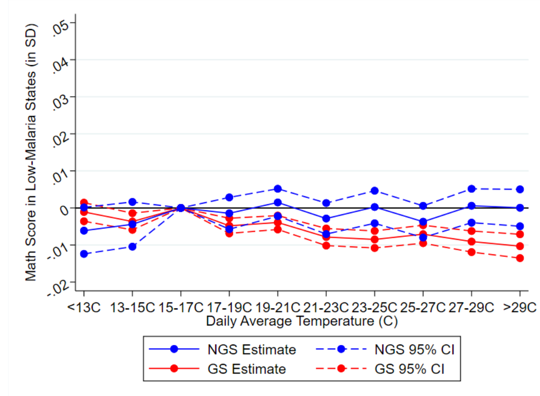
(b) Reading Scores

Notes: The figure shows the effect of longer-run temperature (defined as number of days in the previous calendar year—see figure 4.4(a)) on math and reading performance divided amongst the school year (July—November) and the non-school year (June, December) within the growing season (June—December). The effect of days between 15°C-17°C is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C. The regressions include district, year and age fixed effects. We control flexibly for precipitation and humidity. Standard errors are clustered at the district level. SY: School year; NSY: Non-School Year.

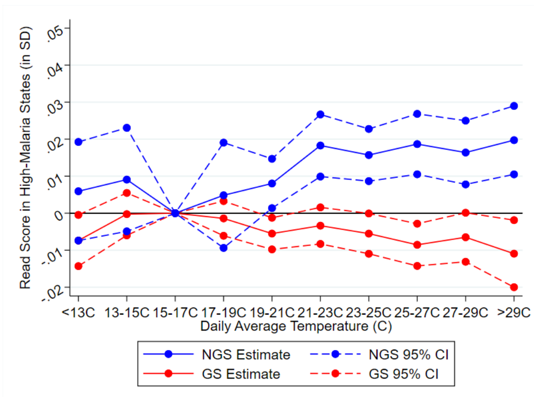
Figure C.13: Previous Year Temperature and Test Scores (ASER) by Malaria Prone States



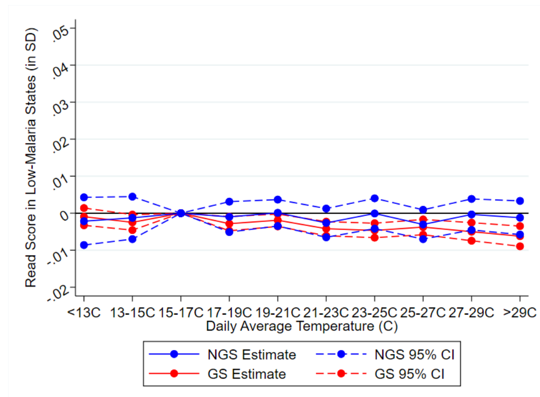
(a) Malaria-Prone States



(b) Other States



(c) Malaria-Prone States



(d) Other States

Notes: This figure shows the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 4.4(a)) on current year math and reading performance by malaria prone states. The malaria prone states are Orissa, Chattisgarh, West Bengal, Jharkhand, and Karnataka. The effect of days between 15°C-17°C is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C. The regressions include district, year and age fixed effects. We control flexibly for precipitation and humidity. Standard errors are clustered at the district level. GS: Growing Season; NGS: Non-Growing Season.

C.5 Tables

Table C.1: On-Track Children: Previous Year Temperature and Test Scores (ASER)

	(1) Math Score (in SD) β / SE	(2) Math Score (in SD) β / SE	(3) Read Score (in SD) β / SE	(4) Read Score (in SD) β / SE
PY Days <15C	-0.0027***		-0.0021***	
	(0.0006)		(0.0005)	
PY Days >21C	-0.0016***		-0.0007*	
	(0.0005)		(0.0004)	
PY Days <13C		-0.0041***		-0.0031***
		(0.0009)		(0.0007)
PY Days 13-15C		-0.0029***		-0.0018**
		(0.0008)		(0.0007)
PY Days 17-19C		-0.0017**		-0.0009
		(0.0009)		(0.0007)
PY Days 19-21C		-0.0010		-0.0003
		(0.0007)		(0.0006)
PY Days 21-23C		-0.0027***		-0.0009
		(0.0008)		(0.0007)
PY Days 23-25C		-0.0030***		-0.0014**
		(0.0008)		(0.0006)
PY Days 25-27C		-0.0022***		-0.0011*
		(0.0008)		(0.0006)
PY Days 27-29C		-0.0025***		-0.0013*
		(0.0008)		(0.0007)
PY Days >29C		-0.0028***		-0.0018**
		(0.0009)		(0.0007)
Observations	3501428	3501428	3501428	3501428
R^2	0.088	0.089	0.065	0.065

Notes: This table shows the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 4.3) on current year math and reading performance for on-track students using the ASER data set. In Columns (2) and (4) (Columns (1) and (3)), the effect of days between 15°C-17°C (15°C-21°C) is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C (15°C-21°C). The regressions include district, year and age fixed effects. We control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered at the district level. PY: Previous Year
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table C.2: Adding Lags: Previous Year Temperature and Test Scores (ASER)

	(1) Math Score (in SD) β / SE	(2) Math Score (in SD) β / SE	(3) Read Score (in SD) β / SE	(4) Read Score (in SD) β / SE
PY Days <15C	-0.0025***		-0.0021***	
	(0.0007)		(0.0006)	
PY Days >21C	-0.0022***		-0.0014***	
	(0.0006)		(0.0005)	
PY Days <13C		-0.0031***		-0.0030***
		(0.0010)		(0.0008)
PY Days 13-15C		-0.0027***		-0.0020**
		(0.0010)		(0.0009)
PY Days 17-19C		-0.0025***		-0.0018**
		(0.0010)		(0.0009)
PY Days 19-21C		-0.0002		-0.0002
		(0.0010)		(0.0009)
PY Days 21-23C		-0.0027***		-0.0016*
		(0.0010)		(0.0009)
PY Days 23-25C		-0.0033***		-0.0024***
		(0.0010)		(0.0008)
PY Days 25-27C		-0.0032***		-0.0024***
		(0.0010)		(0.0009)
PY Days 27-29C		-0.0034***		-0.0023**
		(0.0011)		(0.0009)
PY Days >29C		-0.0035***		-0.0029***
		(0.0010)		(0.0009)
L.2-L.5 Controls	Yes	Yes	Yes	Yes
Observations	4581616	4581616	4581616	4581616
R^2	0.085	0.086	0.069	0.070

Notes: This table shows the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 4.3) on current year math and reading performance using the ASER data set. In Columns (2) and (4) (Columns (1) and (3)), the effect of days between 15°C-17°C (15°C-21°C) is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C (15°C-21°C). The regressions include district, year and age fixed effects. We control flexibly for precipitation and humidity. We also control for lagged temperature, precipitation and humidity. Standard errors are in parentheses, clustered at the district level. PY: Previous Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table C.3: Adding State-Specific Time Trends: Previous Year Temperature and Test Scores (ASER)

	(1) Math Score (in SD) β / SE	(2) Math Score (in SD) β / SE	(3) Read Score (in SD) β / SE	(4) Read Score (in SD) β / SE
PY Days <15C	-0.0032***		-0.0026***	
	(0.0006)		(0.0005)	
PY Days >21C	-0.0025***		-0.0013***	
	(0.0004)		(0.0004)	
PY Days <13C		-0.0036***		-0.0029***
		(0.0008)		(0.0007)
PY Days 13-15C		-0.0023***		-0.0018***
		(0.0008)		(0.0007)
PY Days 17-19C		0.0003		0.0001
		(0.0008)		(0.0008)
PY Days 19-21C		0.0001		0.0004
		(0.0007)		(0.0006)
PY Days 21-23C		-0.0018**		-0.0008
		(0.0007)		(0.0007)
PY Days 23-25C		-0.0024***		-0.0010
		(0.0008)		(0.0007)
PY Days 25-27C		-0.0031***		-0.0017**
		(0.0008)		(0.0007)
PY Days 27-29C		-0.0030***		-0.0014*
		(0.0009)		(0.0008)
PY Days >29C		-0.0032***		-0.0019**
		(0.0009)		(0.0008)
Observations	4581616	4581616	4581616	4581616
R^2	0.097	0.097	0.076	0.076

Notes: This table shows the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 4.3) on current year math and reading performance using the ASER data set. In Columns (2) and (4) (Columns (1) and (3)), the effect of days between 15°C-17°C (15°C-21°C) is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C (15°C-21°C). The regressions include district, year and age fixed effects, and state-specific linear and quadratic trends. We control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered at the district level. PY: Previous Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table C.4: Adding State-Year FE: Longer-Run Temperature and Test Scores (ASER)

	(1) Math Score (in SD) β / SE	(2) Math Score (in SD) β / SE	(3) Read Score (in SD) β / SE	(4) Read Score (in SD) β / SE
PY Days <15C	-0.0015**		-0.0010	
	(0.0007)		(0.0007)	
PY Days >21C	-0.0021***		-0.0014**	
	(0.0006)		(0.0006)	
PY Days <13C		-0.0027***		-0.0021**
		(0.0010)		(0.0009)
PY Days 13-15C		-0.0013		-0.0009
		(0.0008)		(0.0007)
PY Days 17-19C		-0.0008		-0.0009
		(0.0009)		(0.0008)
PY Days 19-21C		-0.0008		-0.0010
		(0.0009)		(0.0008)
PY Days 21-23C		-0.0028***		-0.0022**
		(0.0010)		(0.0009)
PY Days 23-25C		-0.0031***		-0.0025***
		(0.0010)		(0.0009)
PY Days 25-27C		-0.0032***		-0.0026**
		(0.0011)		(0.0010)
PY Days 27-29C		-0.0029**		-0.0023**
		(0.0013)		(0.0011)
PY Days >29C		-0.0031**		-0.0026**
		(0.0014)		(0.0012)
Observations	4581616	4581616	4581616	4581616
R^2	0.102	0.102	0.079	0.079

Notes: This table shows the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 4.3) on current year math and reading performance using the ASER data set. In Columns (2) and (4) (Columns (1) and (3)), the effect of days between 15°C-17°C (15°C-21°C) is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C (15°C-21°C). The regressions include district, age and state-by-year fixed effects. We control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered at the district level. PY: Previous Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table C.5: Nearest (N) Weather Gridpoint and Maximum (M) Daily Temperature: ASER

	(1) Math Score (in SD) β / SE	(2) Math Score (in SD) β / SE	(3) Read Score (in SD) β / SE	(4) Read Score (in SD) β / SE
PY Days <13C N	-0.0023***		-0.0015**	
	(0.0009)		(0.0007)	
PY Days 13-15C N	-0.0027***		-0.0017**	
	(0.0009)		(0.0008)	
PY Days 17-19C N	-0.0008		-0.0003	
	(0.0009)		(0.0008)	
PY Days 19-21C N	-0.0006		0.0006	
	(0.0007)		(0.0006)	
PY Days 21-23C N	-0.0016*		-0.0002	
	(0.0008)		(0.0007)	
PY Days 23-25C N	-0.0023***		-0.0009	
	(0.0008)		(0.0007)	
PY Days 25-27C N	-0.0016**		-0.0007	
	(0.0008)		(0.0006)	
PY Days 27-29C N	-0.0015*		-0.0003	
	(0.0008)		(0.0007)	
PY Days >29C N	-0.0024***		-0.0014*	
	(0.0009)		(0.0008)	
PY Days <17C M		-0.0026***		-0.0016*
		(0.0009)		(0.0008)
PY Days 17-19C M		-0.0033***		-0.0025***
		(0.0009)		(0.0008)
PY Days 21-23C M		-0.0016**		-0.0005
		(0.0008)		(0.0007)
PY Days 23-25C M		-0.0019***		-0.0003
		(0.0007)		(0.0007)
PY Days 25-27C M		-0.0016*		-0.0004
		(0.0008)		(0.0007)
PY Days 27-29C M		-0.0012		0.0001
		(0.0008)		(0.0007)
PY Days 29-31C M		-0.0011		0.0002
		(0.0008)		(0.0007)
PY Days 31-33C M		-0.0017*		-0.0003
		(0.0009)		(0.0008)
PY Days >33C M		-0.0018**		-0.0009
		(0.0009)		(0.0008)
Observations	4581616	4581616	4581616	4581616
R^2	0.084	0.084	0.068	0.068

Notes: This table shows the effects of longer-run temperature (defined as number of days in the previous calendar year) on current year math and reading performance. The regressions include district, year and age fixed effects. We control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered at the district level. PY: Previous Year.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table C.6: Controlling for ASER Weekend Test Month (WTM) Temperature and ASER Weekday Test Month (NWTM) Temperature

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE	(3) Math Score (in SD) β / SE	(4) Read Score (in SD) β / SE
PY Days <13C	-0.0035***	-0.0024***	-0.0023**	-0.0019**
	(0.0009)	(0.0008)	(0.0010)	(0.0009)
PY Days 13-15C	-0.0028***	-0.0019**	-0.0012	-0.0008
	(0.0009)	(0.0009)	(0.0008)	(0.0008)
PY Days 17-19C	-0.0032***	-0.0020**	-0.0011	-0.0009
	(0.0009)	(0.0008)	(0.0009)	(0.0009)
PY Days 19-21C	-0.0005	0.0000	-0.0005	-0.0008
	(0.0008)	(0.0007)	(0.0010)	(0.0009)
PY Days 21-23C	-0.0022***	-0.0008	-0.0022**	-0.0017*
	(0.0008)	(0.0008)	(0.0010)	(0.0009)
PY Days 23-25C	-0.0031***	-0.0018**	-0.0028**	-0.0021**
	(0.0008)	(0.0008)	(0.0011)	(0.0010)
PY Days 25-27C	-0.0022***	-0.0014*	-0.0029**	-0.0022**
	(0.0008)	(0.0008)	(0.0012)	(0.0010)
PY Days 27-29C	-0.0024**	-0.0014	-0.0025*	-0.0017
	(0.0009)	(0.0009)	(0.0013)	(0.0011)
PY Days >29C	-0.0033***	-0.0023***	-0.0027*	-0.0021*
	(0.0010)	(0.0009)	(0.0014)	(0.0012)
CY WTM Days <13C	-0.0076	-0.0042	-0.0196**	-0.0141
	(0.0095)	(0.0088)	(0.0097)	(0.0093)
CY WTM Days 13-15C	-0.0145**	-0.0097*	-0.0101*	-0.0081
	(0.0058)	(0.0052)	(0.0058)	(0.0055)
CY WTM Days 17-19C	-0.0198***	-0.0158***	-0.0052	-0.0077*
	(0.0046)	(0.0043)	(0.0048)	(0.0044)
CY WTM Days 19-21C	-0.0327***	-0.0252***	-0.0111*	-0.0124**
	(0.0059)	(0.0055)	(0.0065)	(0.0060)
CY WTM Days 21-23C	-0.0362***	-0.0272***	-0.0085	-0.0092
	(0.0067)	(0.0060)	(0.0067)	(0.0063)
CY WTM Days 23-25C	-0.0381***	-0.0294***	-0.0067	-0.0074
	(0.0073)	(0.0062)	(0.0073)	(0.0069)
CY WTM Days 25-27C	-0.0350***	-0.0274***	-0.0040	-0.0039
	(0.0077)	(0.0065)	(0.0078)	(0.0072)
CY WTM Days 27-29C	-0.0304***	-0.0254***	-0.0026	-0.0025
	(0.0084)	(0.0071)	(0.0086)	(0.0080)
CY WTM Days >29C	-0.0201	-0.0192*	-0.0009	0.0022
	(0.0136)	(0.0115)	(0.0137)	(0.0126)
CY NWTM Days <13C	-0.0008	-0.0013	0.0074*	0.0031
	(0.0046)	(0.0043)	(0.0044)	(0.0040)
CY NWTM Days 13-15C	-0.0055*	-0.0054**	-0.0003	-0.0012
	(0.0029)	(0.0027)	(0.0030)	(0.0027)
CY NWTM Days 17-19C	-0.0016	-0.0002	0.0011	0.0020
	(0.0023)	(0.0021)	(0.0024)	(0.0022)
CY NWTM Days 19-21C	0.0005	0.0045*	0.0038	0.0073***
	(0.0027)	(0.0024)	(0.0029)	(0.0027)
CY NWTM Days 21-23C	0.0053*	0.0074***	0.0013	0.0055*
	(0.0030)	(0.0026)	(0.0033)	(0.0031)
CY NWTM Days 23-25C	0.0064**	0.0074***	-0.0017	0.0036
	(0.0032)	(0.0027)	(0.0036)	(0.0033)
CY NWTM Days 25-27C	0.0071**	0.0070**	-0.0034	0.0019
	(0.0033)	(0.0028)	(0.0038)	(0.0035)
CY NWTM Days 27-29C	0.0039	0.0067**	-0.0027	0.0031
	(0.0037)	(0.0032)	(0.0045)	(0.0041)
CY NWTM Days >29C	-0.0027	0.0016	-0.0061	0.0007
	(0.0056)	(0.0048)	(0.0071)	(0.0063)
Age FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No
State-by-Year FE	No	No	Yes	Yes
Observations	4581616	4581616	4581616	4581616
R^2	0.087	0.070	0.103	0.079

Notes: This table shows the effects of longer-run temperature (defined as number of days in the previous calendar year) on current year math and reading performance. The regressions include district, year and age fixed effects. We control flexibly for precipitation, humidity, and current year temperature in the months before the ASER test months (NTM: January-August). Standard errors are in parentheses, clustered at the district level. PY: Previous Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table C.7: Combined (Older and Younger Cohort) Sample: Longer-Run Temperature and Test Scores (YLS)

	(1) Math Score (in SD) β / SE	(2) Math Score (in SD) β / SE	(3) PPVT Score (in SD) β / SE	(4) PPVT Score (in SD) β / SE
Days Between Two Tests >23C	-0.002***		-0.003***	
	(0.001)		(0.001)	
Day-of-Test >23C	-0.070**		0.054	
	(0.030)		(0.040)	
Days Between Two Tests 23-25C		-0.002***		-0.003***
		(0.001)		(0.001)
Days Between Two Tests 25-27C		-0.002***		-0.004***
		(0.001)		(0.001)
Days Between Two Tests >27C		-0.005***		-0.003***
		(0.001)		(0.001)
Day-of-Test 23-25C		-0.061**		0.038
		(0.030)		(0.039)
Day-of-Test 25-27C		-0.110***		0.156***
		(0.036)		(0.056)
Day-of-Test >27C		-0.078		0.320***
		(0.052)		(0.071)
Observations	5869	5869	6257	6257
R^2	0.050	0.058	0.074	0.079

Notes: This table shows the effect of temperature (defined as number of days in a given bin between successive tests) on math and reading performance using the YLS data set. The effect of days below 23°C is normalized to zero and all other coefficients are interpreted relative to below 23°C. The regressions include individual, day of week, month, cohort, and survey round (age) fixed effects. We control for day-of-test temperatures, and both cumulative and day-of-test precipitation as well as cumulative and day-of-test humidity. Standard errors are in parentheses, clustered by district-week.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table C.8: Cluster-Bootstrapped Standard Errors: Longer-Run Temperature and Test Scores (YLS)

	(1) Math Score (in SD) β / p-value	(2) Math Score (in SD) β / p-value	(3) PPVT Score (in SD) β / p-value	(4) PPVT Score (in SD) β / p-value
Days Between Two Tests >23C	-0.003		-0.004	
	(0.41)		(0.38)	
Days Between Two Tests 23-25C		-0.007		0.000
		(0.09)		(0.93)
Days Between Two Tests 25-27C		-0.002		-0.007
		(0.01)		(0.25)
Days Between Two Tests >27C		-0.008		-0.007
		(0.01)		(0.12)
Observations	2604	2604	2541	2541
R^2	0.766	0.770	0.542	0.547

Notes: This tables shows the effect of longer-run temperature (defined as number of days in a given bin between successive tests) on math and reading performance using the YLS data set. The effect of days below 23°C is normalized to zero and all other coefficients are interpreted relative to below 23°C. The regressions include individual, day of week, month, and survey round (age) fixed effects. We control for day-of-test temperatures, and both cumulative and day-of-test precipitation as well as cumulative and day-of-test humidity. **P-values are in parentheses, obtained from cluster-bootstrapping our standard errors at the district level (200 iterations).**
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table C.9: Longer-Run Temperature and Test Scores (YLS)

	(1) Math Score (in SD) β / SE	(2) Math Score (in SD) β / SE	(3) PPVT Score (in SD) β / SE	(4) PPVT Score (in SD) β / SE
Days Between Two Tests >23C	-0.003***	-0.003***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Day-of-Test >23C		-0.114***		0.042
		(0.043)		(0.057)
Observations	2604	2604	2541	2541
R^2	0.052	0.058	0.073	0.077

Notes: This tables shows the effect of longer-run temperature (defined as number of days in a given bin between successive tests) on math and reading performance using the YLS data set. The effect of days below 23°C is normalized to zero and all other coefficients are interpreted relative to below 23°C. The regressions include individual, day of week, month, and survey round (age) fixed effects. In Columns (1) and (2), we control for cumulative precipitation and humidity. In Columns (2) and (4), we control for day-of-test temperatures, and both cumulative and day-of-test precipitation as well as cumulative and day-of-test humidity. Standard errors are in parentheses, clustered by district-week.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table C.10: Previous and Current Year Temperature, and Student Attendance (ASER)

	(1) Student Attendance Proportion β / SE	(2) Student Attendance Proportion β / SE
PY NGS Days <15C	0.0001	-0.0000
	(0.0005)	(0.0005)
PY NGS Days >21C	0.0003	0.0003
	(0.0004)	(0.0004)
PY GS Days <15C	-0.0005**	-0.0005**
	(0.0002)	(0.0002)
PY GS Days >21C	-0.0005***	-0.0005***
	(0.0002)	(0.0002)
CY NGS Days <15C	-0.0000	-0.0001
	(0.0005)	(0.0006)
CY NGS Days >21C	0.0002	0.0002
	(0.0003)	(0.0003)
CY GS Days <15C	0.0000	-0.0000
	(0.0003)	(0.0003)
CY GS Days >21C	-0.0001	-0.0001
	(0.0002)	(0.0002)
Observations	93432	93432
R^2	0.429	

Notes: This table shows show the effect of previous and current year temperature (defined as number of days in the calendar year—see Figure 4.3) on current year student attendance in public schools divided amongst the growing season (June—Dec) and the non-growing season (March—May). The effect of days between 15°C-21°C is normalized to zero and all other coefficients are interpreted relative to 15°C-21°C. The regressions include district and year fixed effects. We control flexibly for precipitation and humidity. Column (1) presents results from an OLS regression, while Column (2) presents results from a tobit specification censored at 1 (100%). Standard errors are clustered at the district level. GS: Growing Season; NGS: Non-Growing Season; PY: Previous Year; CY: Current Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table C.11: Previous Year Temperature and Body Mass Index (BMI) (YLS)

	(1) BMI β / SE	(2) BMI-for-Age Z-Score β / SE
PY Days 23-25C	-0.015***	-0.009***
	(0.004)	(0.002)
PY Days 25-27C	-0.023***	-0.015***
	(0.004)	(0.003)
PY Days >27C	-0.025***	-0.018***
	(0.005)	(0.004)
Observations	3460	3460
R^2	0.342	0.080

Notes: This table shows the effect of longer-run temperature (defined as number of days in the previous calendar year) on BMI using the YLS data set. The effect of days below 23°C is normalized to zero and all other coefficients are interpreted relative to below 23°C. The regressions include individual, day of week, month, and survey round (age) fixed effects. We control for cumulative precipitation and humidity. Sample only includes only a balanced panel of school-age children. Robust standard errors are in parentheses. PY: Previous Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table C.12: Previous and Current Year Temperature, and Teacher Attendance (ASER)

	(1) Teacher Attendance Proportion β / SE	(2) Teacher Attendance Proportion β / SE
PY Days <15C	0.0001	0.0003
	(0.0002)	(0.0005)
PY Days >21C	0.0001	0.0006
	(0.0001)	(0.0004)
CY Days <15C	0.0002	0.0005
	(0.0002)	(0.0005)
CY Days >21C	0.0000	0.0004
	(0.0001)	(0.0004)
Observations	75328	75328
R^2	0.052	

Notes: This tables shows the effect of previous and current year temperature (defined as number of days in a given bin between successive tests) on teacher attendance at public schools using the ASER data set. The effect of days between 15°C-21°C is normalized to zero and all other coefficients are interpreted relative to 15°C-21°C. The regressions include district and year fixed effects. We control flexibly for precipitation and humidity. Column (1) presents results from an OLS regression, while Column (2) presents results from a tobit specification censored at 1 (100%). Standard errors are clustered at the district level. PY: Previous Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table C.13: Falsification Test: Future Temperature Doesn't Negatively Impact Prior Yields

	(1) Top 6 Crops Log(Yield) β / SE	(2) Top 6 Crops Lag Log (Yield) β / SE	(3) Top 5 Monsoon Crops Log (Yield) β / SE	(4) Top 5 Monsoon Crops Lag Log (Yield) β / SE
GS Days <13C	-0.0018	-0.0000	-0.0023	0.0007
	(0.0014)	(0.0008)	(0.0019)	(0.0009)
GS Days 13-15C	0.0004	-0.0006	0.0029***	-0.0003
	(0.0009)	(0.0009)	(0.0009)	(0.0012)
GS Days 17-19C	-0.0013	0.0010	-0.0026	0.0029
	(0.0011)	(0.0007)	(0.0025)	(0.0020)
GS Days 19-21C	-0.0032***	0.0023	-0.0033**	0.0053
	(0.0010)	(0.0014)	(0.0015)	(0.0033)
GS Days 21-23C	-0.0027**	0.0031*	-0.0033*	0.0062
	(0.0011)	(0.0017)	(0.0016)	(0.0037)
GS Days 23-25C	-0.0033**	0.0035*	-0.0040**	0.0067*
	(0.0012)	(0.0018)	(0.0016)	(0.0035)
GS Days 25-27C	-0.0042***	0.0026*	-0.0038**	0.0054*
	(0.0012)	(0.0014)	(0.0013)	(0.0031)
GS Days 27-29C	-0.0055***	0.0023	-0.0042***	0.0053
	(0.0010)	(0.0016)	(0.0011)	(0.0032)
GS Days >29C	-0.0096***	0.0017	-0.0116***	0.0044
	(0.0023)	(0.0017)	(0.0035)	(0.0033)
NGS Days <13C	0.0021	0.0034	0.0004	-0.0006
	(0.0021)	(0.0020)	(0.0015)	(0.0013)
NGS Days 13-15C	-0.0023*	-0.0012	0.0003	-0.0058
	(0.0013)	(0.0026)	(0.0019)	(0.0039)
NGS Days 17-19C	-0.0035**	-0.0012	-0.0042	0.0004
	(0.0016)	(0.0011)	(0.0026)	(0.0020)
NGS Days 19-21C	-0.0029*	0.0002	-0.0028	-0.0008
	(0.0016)	(0.0015)	(0.0016)	(0.0021)
NGS Days 21-23C	-0.0021	-0.0009	-0.0016	-0.0014
	(0.0012)	(0.0014)	(0.0017)	(0.0019)
NGS Days 23-25C	-0.0009	-0.0030	-0.0012	-0.0037
	(0.0015)	(0.0017)	(0.0019)	(0.0023)
NGS Days 25-27C	-0.0015	-0.0025	-0.0021	-0.0029
	(0.0017)	(0.0021)	(0.0023)	(0.0026)
NGS Days 27-29C	-0.0010	-0.0005	-0.0018	-0.0006
	(0.0019)	(0.0022)	(0.0024)	(0.0028)
NGS Days >29C	-0.0018	-0.0030	-0.0028	-0.0030
	(0.0020)	(0.0022)	(0.0025)	(0.0028)
Observations	9479	9479	9475	9475
R^2	0.885	0.878	0.877	0.870

Notes: This table examines the effect of hot days on contemporaneous (columns (1) and (3)) and past (columns (2) and (4)) yields. The effect of days between 15°C-17°C is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C. The regressions include district, year and age fixed effects, and control for age-for-grade status. We also control flexibly for precipitation. Standard errors are in parentheses, clustered at the state level. GS: Growing Season, NGS: Non-Growing Season

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table C.14: Future Temperature Shocks Are Uncorrelated With Baseline Heat Resistant Crop Adoption

	(1)	(2)	(3)	(4)	(5)
	2006	2007	2008	2009	2010
	β / SE	β / SE	β / SE	β / SE	β / SE
PY Days <15C (Residualized)	0.0001	-0.0024	-0.0014	0.0030	0.0021
	(0.0022)	(0.0032)	(0.0035)	(0.0035)	(0.0021)
PY Days >21C (Residualized)	-0.0018	0.0027	0.0051**	-0.0062***	-0.0003
	(0.0021)	(0.0020)	(0.0024)	(0.0021)	(0.0027)
Observations	525	536	539	541	538
R^2	0.010	0.049	0.036	0.038	0.020

	(6)	(7)	(8)	(9)
	2011	2012	2013	2014
	β / SE	β / SE	β / SE	β / SE
PY Days <15C (Residualized)	-0.0083***	-0.0022	0.0019	0.0023
	(0.0030)	(0.0037)	(0.0024)	(0.0031)
PY Days >21C (Residualized)	0.0050**	0.0005	0.0018	-0.0011
	(0.0022)	(0.0025)	(0.0018)	(0.0030)
Observations	525	528	515	537
R^2	0.055	0.012	0.023	0.011

Notes: This table examines if residualized adoption of heat-resistant crops (binary indicator for above median adoption as used in main-analysis) co-varies with number of hot days in the previous year. The effect of days between 15°C-17°C is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C. The regressions include district, year and age fixed effects, and control for age-for-grade status. We also control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered at the district level. PY: Previous Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table C.15: Does NREGA rollout co-vary with hot days in the previous year?

	(1) NREGA (0/1) β / SE
PY Days <13C	0.0005
	(0.0034)
PY Days 13-15C	-0.0029
	(0.0042)
PY Days 17-19C	-0.0022
	(0.0037)
PY Days 19-21C	-0.0059*
	(0.0032)
PY Days 21-23C	-0.0004
	(0.0032)
PY Days 23-25C	0.0003
	(0.0033)
PY Days 25-27C	0.0029
	(0.0035)
PY Days 27-29C	0.0061
	(0.0038)
PY Days >29C	0.0030
	(0.0039)
Observations	1306
R^2	0.698

Notes: This table examines if NREGA rollout co-varies with number of hot days in the previous year. Regression includes districts and year fixed effects. We control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered at the district level.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

Table C.16: Triple Difference: Previous Year Temperature, NREGA, and Test Scores

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
PY Days >21C	-0.0011	-0.0008
	(0.0009)	(0.0007)
NREGA PY	-0.1965***	-0.1363**
	(0.0596)	(0.0573)
NREGA PY * PY Days >21C	0.0006***	0.0004**
	(0.0002)	(0.0002)
Observations	1866623	1866623
R^2	0.177	0.167

Notes: This table shows the influence of NREGA in attenuating the effects of longer-run temperature (defined as number of days in the previous calendar year—see Figure 4.3) on current year math and reading performance. The effect of days between 15°C-21°C is normalized to zero and all other coefficients are interpreted relative to 15°C-21°C. The regressions include district, year and age fixed effects, and control for age-for-grade status. We also control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered at the district level. PY: Previous Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Appendix D

Chapter 4 of appendix

D.1 Alternative Explanations

In this section, we rule out some alternative channels that could potentially explain the observed relationship between temperature and agricultural input use. Specifically, we consider two alternative explanations: (1) influence of humidity on the incidence of pests and crop disease, and (2) higher than normal temperatures affecting soil moisture, in turn reducing fertilizer uptake.

Humidity

Grey leaf spot is a major maize disease in Kenya. Empirical results suggest that moderate to high temperatures and prolonged periods of high relative humidity are both favorable for the development of gray leaf spot (241; 336). Similarly, relative humidity is also a main factor affecting the distribution of stem borers, the main insect pest affecting maize in Kenya (282). Thus, given the correlation between heat and humidity, it is possible that our estimates actually capture the influence of relative humidity on pests and crop diseases. To rule out this explanation, we control for relative humidity at the village level, and find that our estimates are relatively unchanged (Table D.30). Even holding humidity constant, temperature exerts an independent effect on agricultural input use.

Soil Moisture

Higher than normal temperatures could reduce the stock of water in the soil, and thereby reduce fertilizer effectiveness, inducing lower farmer uptake. Water and soil nutrients (such as nitrogen and phosphorus) are essential for crop growth. Fertilizer use adds to soil nutrients. In rain-fed agriculture, where soil moisture depends on rainfall, temperature, and soil quality, the effectiveness of fertilizer can be seriously affected by inadequate soil moisture. When moisture deficiency is the primary factor limiting crop growth, yield is less responsive to fertilizer use, in line with von Liebig's law of the minimum which states that yield is determined by the amount of the most limiting nutrient (262; 304). In addition, soil nutrients are taken up by plant roots in a water solution, so water availability affects how efficiently applied fertilizer can be used by crops. Farmers are less likely to adopt fertilizer in zones where soil moisture supply is deficient (at least partially) due to low yield response to fertilizer (223; 244; 263; 404).

Moreover, both air temperature and soil temperature affect soil moisture through the evapotranspiration process, the predominant water cycle in the absence of precipitation (251). Temperature plays a critical role in evapotranspiration. Higher temperature increases transpiration of water in the surface soil, just like in the plants. (234) assess the implications of climate change for soil moisture availability in southeast Turkey, finding substantial reductions in availability during summer. Local effects of heat stress on soil moisture will also vary with soil characteristics. (63), for example, show that the infiltration and the water-holding capacity of soils on limestone are greater with increased frost activity and infer that increased temperatures could lead to increased surface or shallow runoff.

Since we include village fixed effects in our model, we control for time invariant qualities of the soil. We also control for time varying attributes of soil at province level via province-round fixed effects. However, if changes in heat across years are correlated with changes in soil moisture within a province, the estimated relationship between temperature and fertilizer use may be susceptible to the soil moisture channel. To rule out this explanation, we control for daily soil moisture at the village level. Our findings remain unchanged when we hold soil moisture constant (Table D.31).[1]

D.2 The Effects of Rainfall on Pesticides and Fertilizer Use

In Table D.32 and D.33 we report the coefficients on the upper and lower rainfall terciles for each period within the agricultural growing season. The effects

[1] Unfortunately, daily soil moisture data could not be obtained for the entire sample.

are as one would expect. High rainfall (upper tercile) is commonly associated with greater leaching and lowered effectiveness of pesticide applications once plants have emerged (in GS2), so farmers predictably reduce pesticide application in the wettest years. Conversely, in the driest years, the risk of top dressing fertilizer damaging maize increases, to farmers optimally respond by reducing fertilizer application in the driest (lowest rainfall tercile) seasons.[2] The weeding labor effect in GS1 likely reflects farmers' efforts to reduce weed competition with newly planted seed and emergent seedlings when they face moisture stress. The yield effects of rainfall are likewise as one would predict. And the core results on which we focus are unchanged by including the upper and lower rainfall terciles. We now include these results in the appendix and briefly discuss them in the revised manuscript.

D.3 Protective Effects of Adaptation

In Table D.22, we estimate a reduced form relationship between temperatures in the growing season and maize yields; that is, we observe the net effect of at least the following channels of impact: an increase in incidence of pests, weeds and crop diseases, consequent increase in pesticide use and manual weeding, decrease in fertilizer use, and an unlikely direct effect of higher temperatures

[2]The GS1 rain top tercile point estimate on fertilizer may reflect that early in what seems like a good season (solid rainfall) farmers might try going without fertilizer. Indeed, the qualitative evidence from the TAMPA data set supports such an explanation: almost 40% of all non-adopters of fertilizer claimed they had no need to use fertilizer. Alternatively, it could be that fertilizer response is pretty sensitive to soil conditions and anything outside of the regular rainfall zone causes farmers to worry that they will either waste the fertilizer (if it leaches away with too much rainfall) or burn the crop (if there is too little rainfall).

on maize yields.[3] We find an extra degree day over 8C in the initial growth stage (GS1) reduces maize yields by 0.38%. At baseline (round 1), the average maize output was roughly 292 kg/acre. Therefore, 0.38% corresponds to 1.1 kg/acre decrease in output. We find an extra degree day over 8C in the initial growth stage (GS1) increases pesticide use by 2.14% and reduces fertilizer use by 1.31% (Table 5.1).[4]

Existing evidence strongly suggests that fertilizer and pesticide applications are associated with large productivity gains for maize farmers in Kenya. (262) estimate the mean marginal physical product of 17.64 kg maize/kg nitrogen fertilizer. (142) show 1 teaspoon fertilizer applied to each plant increases maize yield by 63%. Tests in Zambia indicate maize yield differences in sprayed and unsprayed fungicide treatments range from 27 to 54% (171). In Zimbabwe, research with herbicides resulted in yield increases of up to 50% in maize. Use of herbicides in Kenyan weed trials resulted in 33% higher maize yields than with the farmer practice of hand weeding on account of better weed control (172). Unfortunately, to our knowledge, there exist no studies that examine the intensive margin effects of pesticide use on agricultural yields in developing countries.

Therefore, we present back-of-the-envelope calculations using agricultural input productivity estimates from the TAMPA data. We estimate the intensive-margin effects of pesticide and fertilizer applications on maize yields after absorbing household-specific time invariant unobservables via household fixed

[3] Average daily temperatures in the data are less than 30C. In fact, the 99th percentile of the distribution of daily *maximum* temperatures for villages in our sample is 32C. This is significant since optimum maize growth occurs at temperatures of 24-30C (319). Relatedly, (345) and (249) find that maize yields only decline physiologically due to heat stress above 29-30C.

[4] At baseline, the average maize farmer used 0.24 kg/acre of pesticides and 46.07 kg/acre of fertilizer. Therefore, an extra degree day over 8C in the initial growth stage (GS1) increased pesticide use by 0.005 kg/acre and reduced fertilizer use by 0.6 kg/acre.

effects and village-specific time varying confounders via village-by-round fixed effects (Table D.34). We find a 1% increase in pesticide (fertilizer) application is associated with a 2.7% (3.5%) increase in maize yields. It is important to note these estimates may be biased upwards due to household-specific time varying unobservables correlated with maize yields and adoption of modern agricultural technologies (e.g., household-specific transitory income shocks).

A 1.31% decrease in fertilizer use decreases maize yields by 4.56% or 13.39 kg/acre and a 2.14% increase in pesticide use increases maize yields by 5.78% or 16.87 kg/acre. The decrease in maize yields in presence of an extra DD over 8C, and the consequent agricultural adaptation, is 1.1 kg/acre **(Qn. C)**. If the average maize farmer did not adjust production decisions in response to an extra DD increase in temperature over 8C, maize yields would decline by 4.58 kg/acre (-1.1 - 16.87 + 13.39) **(Qn. B)**. Lastly, maize yield would increase by 13.39 kg/acre if the average maize farmer did not experience an extra DD over 8C **(Qn. A)**.

Therefore, defensive investments undertaken by the average maize farmer in response to an extra DD over 8C protected 3.48 kg of maize yield/acre, roughly 75% of expected loss.

D.4 Figures

Figure D.1: Location of Sample Villages

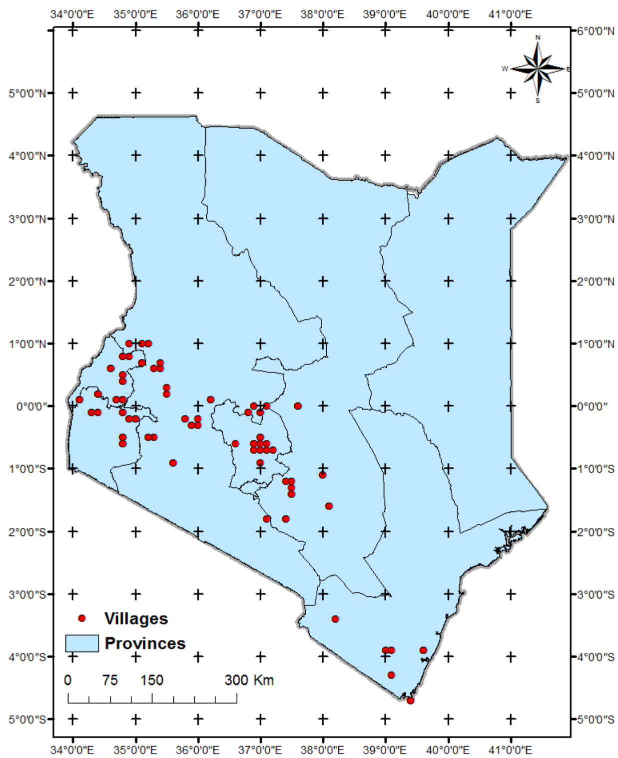


Figure D.2: Maize Calendar in Sample Villages

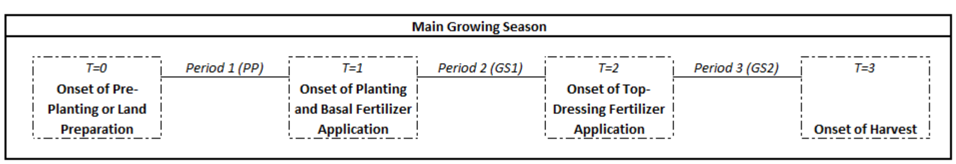
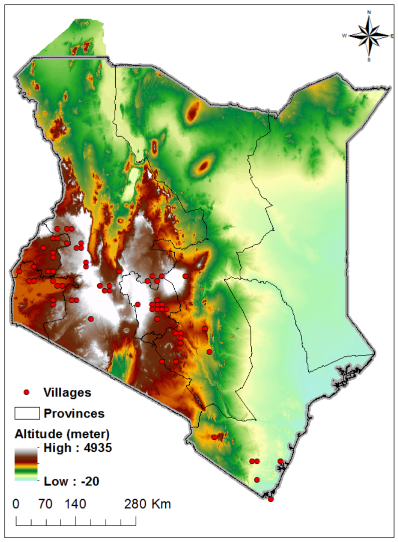
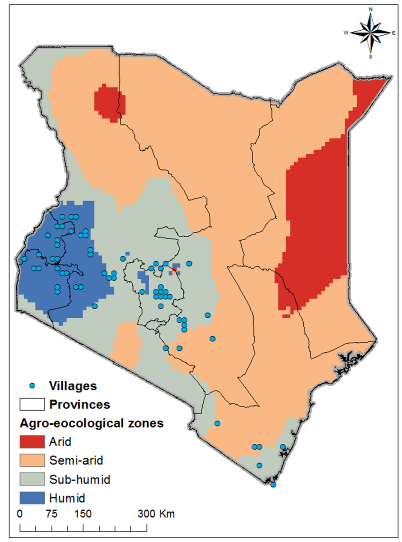


Figure D.3: Spatial Variation in Altitude and Agro-Ecological Zones across TAMPA Villages



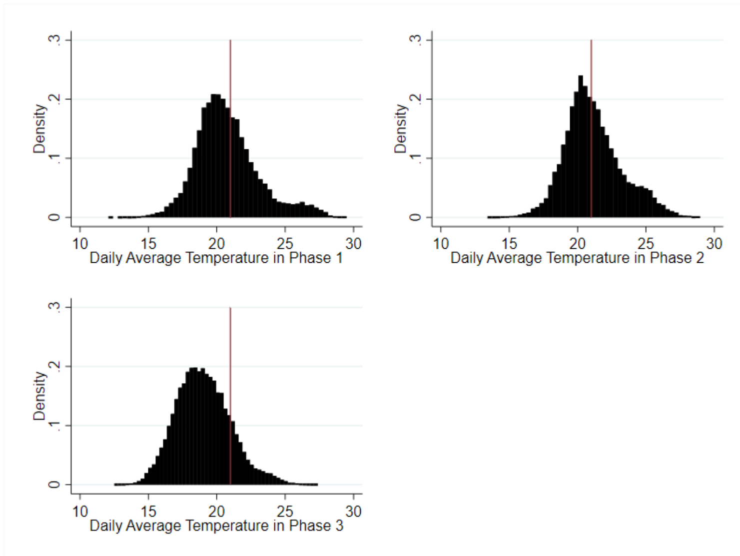
(a) Altitude



(b) Agro-Ecological Zones

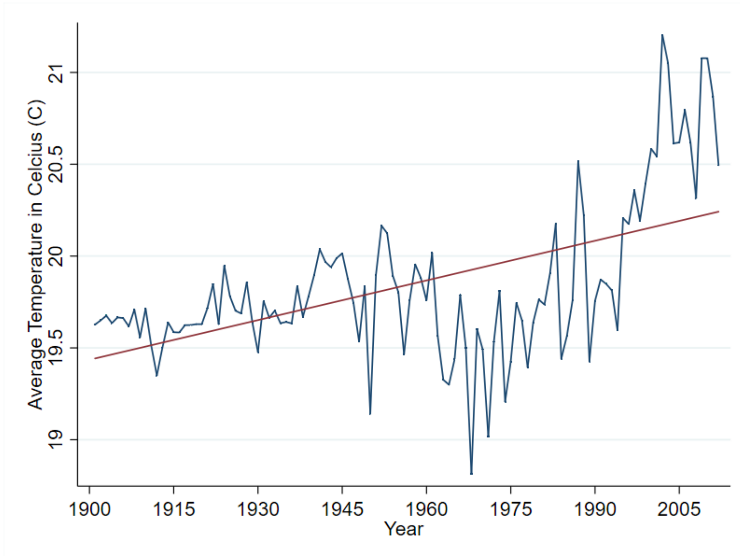
Notes: This figure shows spatial variation in altitude and agro-ecological zones across TAMPA villages.

Figure D.4: Daily Average Temperature by Phases in the Agricultural Cycle (1990-2012)



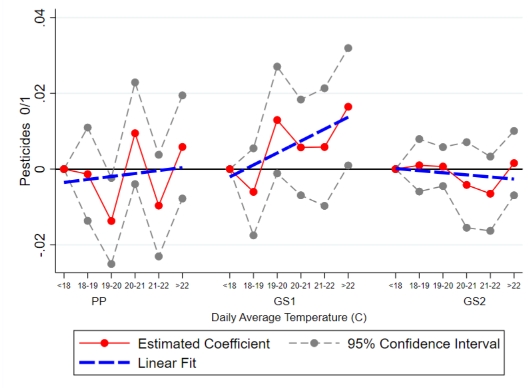
Notes: Distribution of average daily temperatures from 1990-2012 for three phases of the agricultural cycle. Phase 1: pre-planting or land preparation - onset of planting; Phase 2: planting or basal fertilizer application - onset of top dressing fertilizer; Phase 3: top dressing fertilizer application - onset harvest. We calculate cumulative growing degree days from a lower bound of 8C (represented by red vertical line)

Figure D.5: Historical Temperature Trends in Kenya (1901-2012)

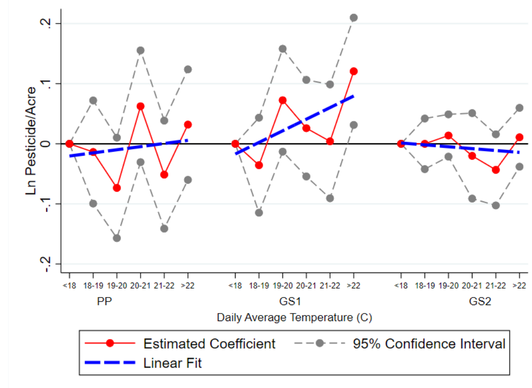


Notes: This figure presents average yearly temperatures as well as the linear fit for villages in the TAMPA sample generated using monthly average temperatures from the Climate Research Unit Time Series Grid Version 3.23 at the University of East Anglia.

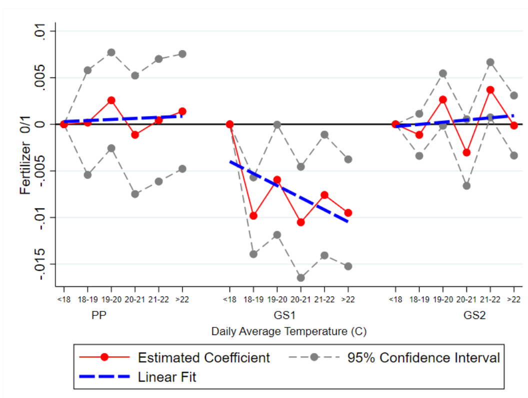
Figure D.6: Temperature Bins | Household FE: Temperature, Fertilizer and Pesticide Use



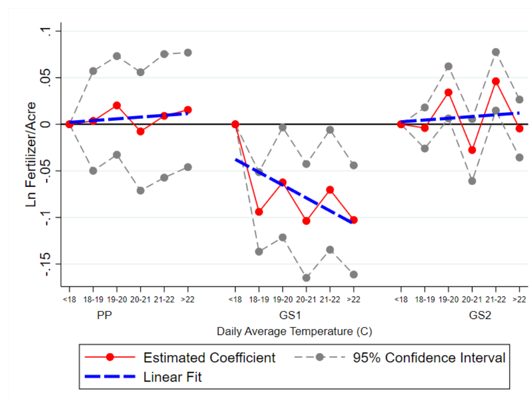
(a) Pesticides 0/1



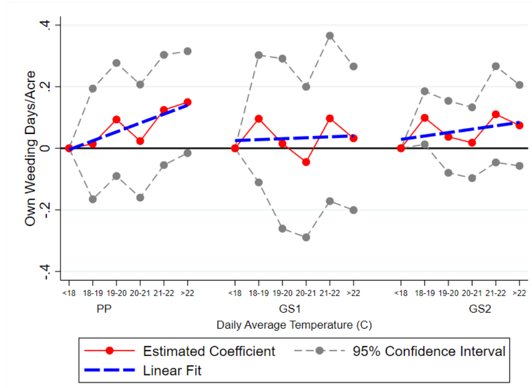
(b) Ln Pesticide/Acre



(c) Fertilizer 0/1



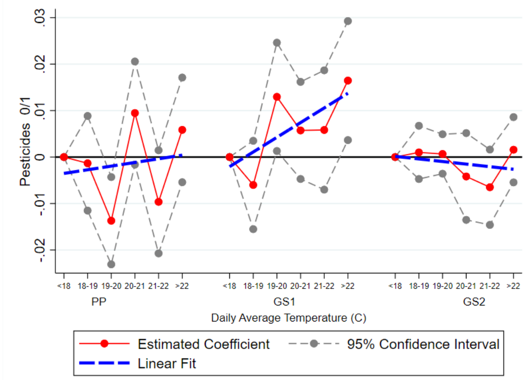
(d) Ln Fertilizer/Acre



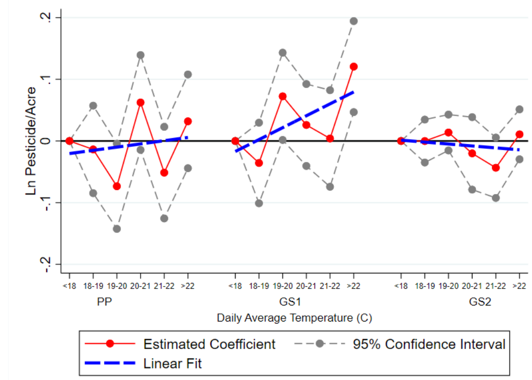
(e) Own Weeding Days/Acre

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use and 3 survey rounds (2003-04, 2006-07 and 2009-10) for pesticides and weeding labor days. The figure presents the effects of temperature (captured via number of days in each temperature bin) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. All figures include household and province-by-year fixed effects as well as controls for precipitation. Standard errors are clustered by village.

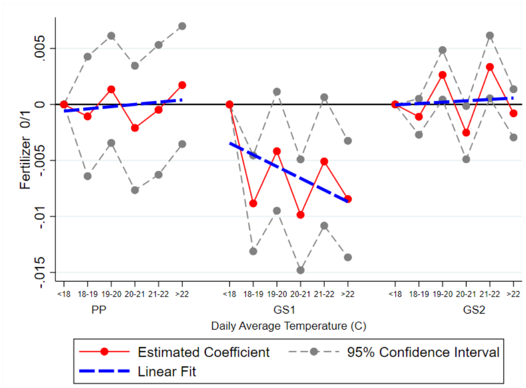
Figure D.7: Temperature Bins | Province-Specific Time Trends: Temperature, Fertilizer and Pesticide Use



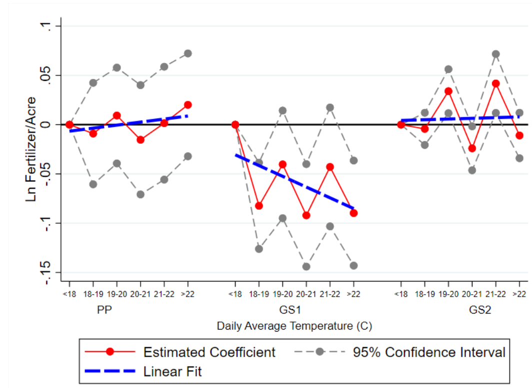
(a) Pesticides 0/1



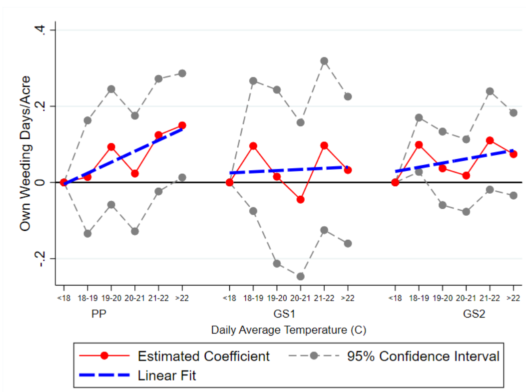
(b) Ln Pesticide/Acre



(c) Fertilizer 0/1



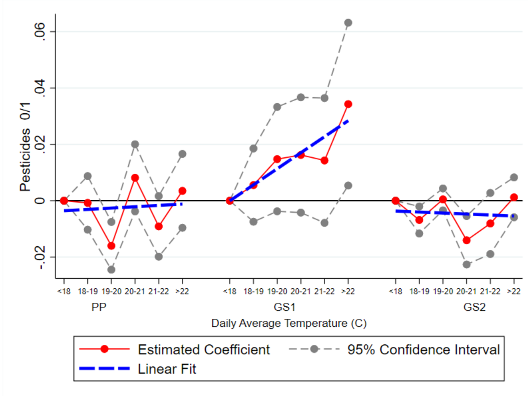
(d) Ln Fertilizer/Acre



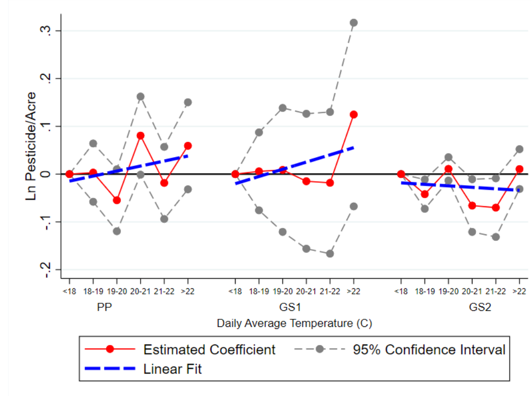
(e) Own Weeding Days/Acre

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use and 3 survey rounds (2003-04, 2006-07 and 2009-10) for pesticides and weeding labor days. The figure presents the effects of temperature (captured via number of days in each temperature bin) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. All figures include village fixed effects and province-specific (linear, quadratic, and cubic) time trends as well as controls for precipitation. Standard errors are clustered by village.

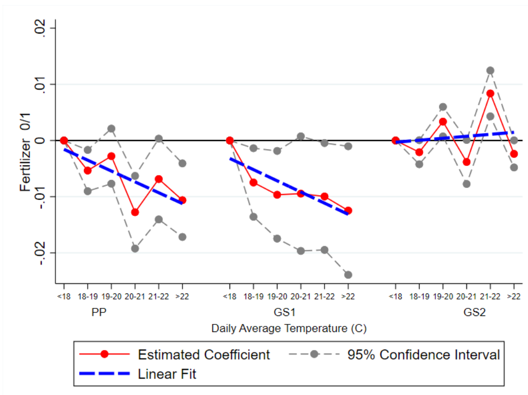
Figure D.8: Temperature Bins | District*Year FE: Temperature, Fertilizer and Pesticide Use



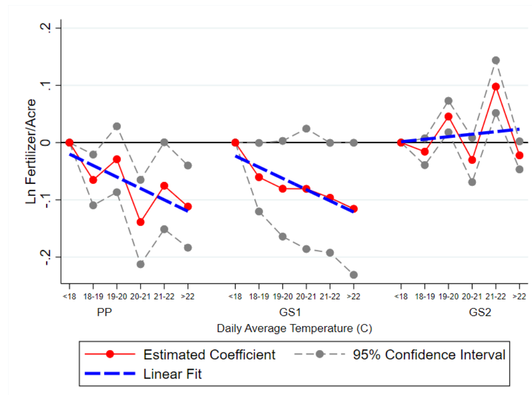
(a) Pesticides 0/1



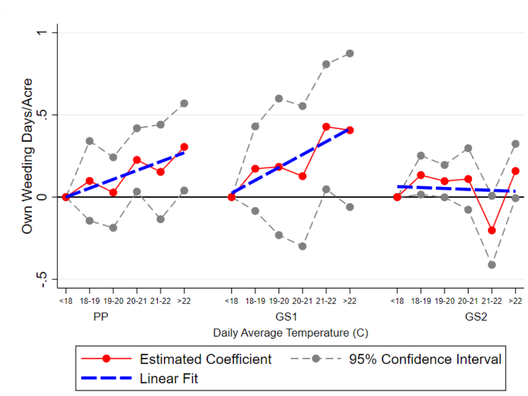
(b) Ln Pesticide/Acre



(c) Fertilizer 0/1



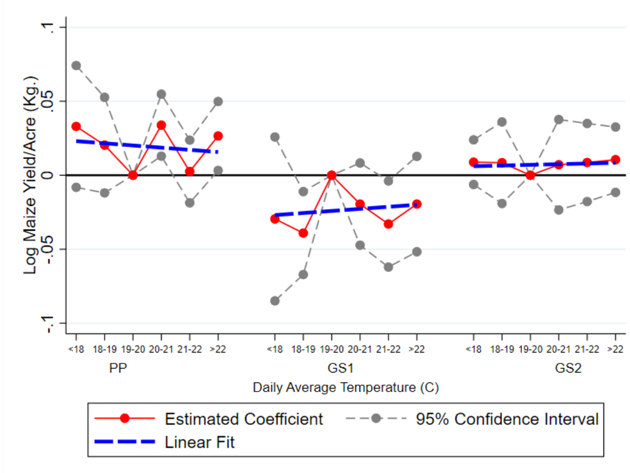
(d) Ln Fertilizer/Acre



(e) Own Weeding Days/Acre

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use and 3 survey rounds (2003-04, 2006-07 and 2009-10) for pesticides and weeding labor days. The figure presents the effects of temperature (captured via number of days in each temperature bin) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. All figures include village and district-by-year fixed effects as well as controls for precipitation. Standard errors are clustered by village.

Figure D.9: Temperature Bins: Log Total Maize Output and Temperature



Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10). The figure presents the effects of temperature (captured via number of days in each temperature bin) on on total maize output. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. All figures include village and province-by-year fixed effects as well as controls for precipitation. Standard errors are clustered by village.

D.5 Tables

Table D.1: Summary Statistics

	1997	2000	2004	2007	2010
Pesticides 0/1			0.27	0.65	0.53
			(0.45)	(0.48)	(0.50)
Pesticide/Acre(kgs)			0.24	0.50	0.56
			(1.68)	(1.01)	(3.96)
Total Weeding Days/Acre			9.59	4.67	4.56
			(11.64)	(6.94)	(6.43)
Own Weeding Labor 0/1			0.92	0.80	0.77
			(0.27)	(0.40)	(0.42)
Own Weeding Days/Acre			7.86	3.64	3.16
			(11.11)	(6.13)	(5.35)
Hired Weeding Labor 0/1			0.25	0.21	0.20
			(0.43)	(0.41)	(0.40)
Hired Weeding Days/Acre			1.73	1.04	1.41
			(4.80)	(3.75)	(4.08)
Fertilizer 0/1	0.63	0.69	0.71	0.75	0.75
	(0.48)	(0.46)	(0.45)	(0.43)	(0.44)
Fertilizer/Acre(kgs)	46.07	57.48	51.37	54.53	51.25
	(76.02)	(91.09)	(70.20)	(63.80)	(57.05)
Maize Output/Acre(kgs)	292.33	355.18	406.68	489.37	394.87
	(333.03)	(908.16)	(424.91)	(445.54)	(353.66)

Notes: Standard deviations are given in parentheses. Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10). Detailed data on pesticides and weeding labor days was only collected in 2003-04, 2006-07 and 2009-10.

Table D.2: Pesticide Use Transitions

	Fraction of Households
NNN	0.22
	(0.42)
NYY	0.26
	(0.44)
NNY	0.08
	(0.27)
NYN	0.16
	(0.37)
YNY	0.02
	(0.15)
YNN	0.02
	(0.15)
YYN	0.07
	(0.25)
YYY	0.17
	(0.37)
Observations	1242

Notes: This table shows all possible three transitions in our sample of farmers and the fraction of our sample that experiences each of these transitions. The three periods correspond to the 2003-04, 2006-07 and 2009-10 survey rounds. In the first column, the three letters represent the transition history with respect to pesticide adoption, where "Y" represents the use of pesticides and "N" represents non-adoption of pesticides. These are ordered by survey round. For example, the transition "YYY" stands for farmers who used pesticides in all three periods; they make up about 17% of our sample. "YYN" represents the 7% of the sample that use pesticides in 2003-04 and 2006-07 but not in 2009-10.

Table D.3: Fertilizer Use Transitions

	Fraction of Households
NNNNN	0.16
	(0.37)
NYYYY	0.06
	(0.23)
NNYYY	0.03
	(0.17)
NNNYY	0.02
	(0.12)
NNNNY	0.03
	(0.16)
NYN/YNY	0.14
	(0.35)
YNNNN	0.00
	(0.07)
YYNNN	0.01
	(0.07)
YYYNN	0.00
	(0.04)
YYYYN	0.02
	(0.12)
YYYYY	0.54
	(0.50)
Observations	1242

Notes: This table shows all possible five transitions in our sample of farmers and the fraction of our sample that experiences each of these transitions. The three periods correspond to the 1996-97, 1999-00, 2003-04, 2006-07 and 2009-10 survey rounds. In the first column, the five letters represent the transition history with respect to fertilizer adoption, where "Y" represents the use of pesticides and "N" represents non-adoption of fertilizer. For example, the transition "YYYYY" stands for farmers who used fertilizer in all five periods; they make up about 54% of our sample. "NYN/YNY" stands for farmers who transitioned both in and out of fertilizer use within these five rounds of data. All other sequences are unidirectional.

Table D.4: Maize Crop Calendar Across Provinces

	Eastern	Western	Coast	Central	Nyanza	Rift Valley	
	1st Jun/1st Aug	1st Jan/15th Jan	15th Jan	1st Jan/15th Jan	1st Jan	1st Jan/15th Jan	Pre-Planting
PP							
	1st Aug/1st Oct	15th Feb/1st Mar/15th Mar	15th Mar	15th Feb/1st Mar/15th Mar	15th Feb/1st Mar	1st Mar/15th Mar	Planting
GS1							
	16th Oct/22nd Oct/1st Nov	1st Apr/16th Apr	1st May	1st Apr/16th Apr	1st Apr	1st Apr/6th Apr/16th Apr	Post-Planting
GS2							
	15th Dec/31st Dec	1st Aug	15th Jul	1st Aug/1st Sep	1st Jul/1st Aug	15th Jul/1st Aug/1st Sep	Harvest

Notes: The table presents maize crop calendars across provinces in Kenya. PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest.

Table D.5: Growing Degree Days: Mean and Standard Deviations – Rounds 1-5

	All	1997	2000	2004	2007	2010
CY PP DD >8C	746.57	743.48	744.48	732.39	778.31	734.17
	(127.74)	(125.46)	(125.84)	(129.89)	(127.41)	(124.80)
CY GS1 DD >8C	489.06	480.81	474.85	504.17	481.38	504.07
	(220.00)	(214.76)	(221.84)	(223.81)	(213.96)	(223.96)
CY GS2 DD >8C	1143.27	1157.08	1136.57	1130.27	1142.41	1150.01
	(278.22)	(282.89)	(280.64)	(272.49)	(283.07)	(271.42)
Observations	6210	1242	1242	1242	1242	1242

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10). Temperature data was generated at the village level, so the table reports mean and standard deviations for degree days (DD) over 8C for each survey round. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard deviations are in parentheses.

Table D.6: Climate Change in Kenya?

	(1) Farmer Noticed Change in Temperature?	(2) Famer Affected by Changes in Temperature?
2009		
No	53.14	17.70
Yes	46.86	82.30

Notes: Sample includes 1242 households, balanced over 5 survey rounds, in the 2009-10 TAMPA survey.

Table D.7: How was farming affected by this change in temperature?

	(1) Affected by Changes in Temperature, How?
2009	
Decline in Yields	44.68
Decrease in Land Quality	4.38
Difficult to Time Seasons	6.89
Increase in Yields	5.43
Other	1.88
Weeds/Pests/Diseases	36.74

Notes: Sample includes 1242 households in the 2009-10 TAMPA survey.

Table D.8: Why Didn't You Use Fertilizer?

	(1) Why No Fertilizer?
2009	
Fertilizer Not Available	0.92
Lack of Advice	3.06
No Money/Too Expensive	57.80
No Need To Use Fertilizer	38.23

Notes: Sample includes 1242 households in the 2009-10 TAMPA survey.

Table D.9: Temperature and Log Hired Weeding Labor KES/acre

	(1) OLS β / SE	(2) Tobit β / SE	(3) Honoré's Tobit β / SE
CY PP DD >8C	0.0013	0.0065	0.0045
	(0.0030)	(0.0064)	(0.0059)
CY GS1 DD >8C	0.0119**	0.0255**	0.0204*
	(0.0055)	(0.0112)	(0.0105)
CY GS2 DD >8C	0.0018	0.0037	0.0036
	(0.0020)	(0.0037)	(0.0035)
Village FE	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes
Observations	3726	3726	3726
R^2	0.154		

Notes: Sample includes 1242 households balanced over 3 survey rounds (1996-97, 1999-00, 2003-04, 2006-07. The table presents the effects of temperature (captured via degree days (DD) over 8C) on hired weeding labor. Columns 2 and 3 present Standard Tobit and Honoré Fixed Effects Tobit estimates, respectively. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table D.10: Temperature and Log Total Agricultural Input Expenditures

	(1) Ln Total Input Expenditures/Acre β / SE
CY PP DD >8C	-0.0027
	(0.0019)
CY GS1 DD >8C	-0.0091***
	(0.0028)
CY GS2 DD >8C	-0.0004
	(0.0010)
Village FE	Yes
Province-by-Year FE	Yes
Rainfall Controls	Yes
Observations	3726
R^2	0.428

Notes: Sample includes 1242 households balanced over 3 survey rounds (2003-04, 2006-07 and 2009-10) for agricultural input expenditures. The table presents the effects of temperature (captured via degree days (DD) over 8C) on total agricultural input expenditures/acre. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses. Standard errors are in parentheses, clustered by village.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table D.11: Household FE: Temperature, Fertilizer and Pesticide Use

	(1) Pesticides 0/1 β / SE	(2) Ln Pesticide/Acre β / SE	(3) Fertilizer 0/1 β / SE	(4) Ln Fertilizer/Acre β / SE	(5) Own Weeding Days/Acre β / SE
CY PP DD >8C	0.0010	0.0067	-0.0004	-0.0044	0.0171
	(0.0010)	(0.0070)	(0.0005)	(0.0046)	(0.0104)
CY GS1 DD >8C	0.0027**	0.0214***	-0.0013**	-0.0131**	-0.0068
	(0.0011)	(0.0070)	(0.0006)	(0.0056)	(0.0142)
CY GS2 DD >8C	-0.0005	-0.0022	-0.0000	0.0005	0.0049
	(0.0005)	(0.0035)	(0.0002)	(0.0022)	(0.0075)
Household FE	Yes	Yes	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Observations	3726	3726	6210	6210	3726
R^2	0.586	0.586	0.740	0.789	0.478

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use and 3 survey rounds (2003-04, 2006-07 and 2009-10) for pesticides and weeding labor days. The table presents the effects of temperature (captured via degree days (DD) over 8C) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table D.12: Observed temperature variation: proportion of households with degree-days below/above average (degrees) after removing province-specific time trends, province*year effects and district*year effects

	Removed Prov-Specific Time Trends % HHs	Removed Prov*Round FE % HHs	Removed Dist*Round FE % HHs
CY PP DD >8C: DD below/above 5 degrees	0.76		
CY PP DD >8C: DD below/above 10 degrees	0.50		
CY GS1 DD >8C: DD below/above 5 degrees	0.65		
CY GS1 DD >8C: DD below/above 10 degrees	0.49		
CY GS2 DD >8C: DD below/above 5 degrees	0.78		
CY GS2 DD >8C: DD below/above 10 degrees	0.60		
CY PP DD >8C: DD below/above 5 degrees		0.69	
CY PP DD >8C: DD below/above 10 degrees		0.38	
CY GS1 DD >8C: DD below/above 5 degrees		0.50	
CY GS1 DD >8C: DD below/above 10 degrees		0.21	
CY GS2 DD >8C: DD below/above 5 degrees		0.57	
CY GS2 DD >8C: DD below/above 10 degrees		0.34	
CY PP DD >8C: DD below/above 5 degrees			0.33
CY PP DD >8C: DD below/above 10 degrees			0.15
CY GS1 DD >8C: DD below/above 5 degrees			0.23
CY GS1 DD >8C: DD below/above 10 degrees			0.07
CY GS2 DD >8C: DD below/above 5 degrees			0.33
CY GS2 DD >8C: DD below/above 10 degrees			0.17

Notes: Sample include 1242 balanced households over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10). The table presents the leftover variation in growing degree days (DD) after removing province-specific time trends, province-by-round, and district-by-round fixed effects. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest.

Table D.13: Province-Specific Time Trends: Temperature, Fertilizer and Pesticide Use

	(1) Pesticides 0/1	(2) Ln Pesticide/Acre	(3) Fertilizer 0/1	(4) Ln Fertilizer/Acre	(5) Own Weeding Days/Acre
	β / SE	β / SE	β / SE	β / SE	β / SE
CY PP DD >8C	0.0010	0.0067	-0.0000	0.0001	0.0171**
	(0.0008)	(0.0058)	(0.0003)	(0.0025)	(0.0086)
CY GS1 DD >8C	0.0027***	0.0214***	-0.0010***	-0.0118***	-0.0068
	(0.0009)	(0.0058)	(0.0004)	(0.0036)	(0.0117)
CY GS2 DD >8C	-0.0005	-0.0022	0.0001	0.0015	0.0049
	(0.0004)	(0.0029)	(0.0002)	(0.0015)	(0.0062)
Village FE	Yes	Yes	Yes	Yes	Yes
Prov-Specific Time Trends	Yes	Yes	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Observations	3726	3726	6210	6210	3726
R^2	0.336	0.353	0.593	0.656	0.164

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use and 3 survey rounds (2003-04, 2006-07 and 2009-10) for pesticides and weeding labor days. The table presents the effects of temperature (captured via degree days (DD) over 8C) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table D.14: District*Year FE: Temperature, Fertilizer and Pesticide Use

	(1) Pesticides 0/1	(2) Ln Pesticide/Acre	(3) Fertilizer 0/1	(4) Ln Fertilizer/Acre	(5) Own Weeding Days/Acre
	β / SE	β / SE	β / SE	β / SE	β / SE
CY PP DD >8C	0.0007	0.0089	-0.0019***	-0.0220***	0.0326*
	(0.0011)	(0.0065)	(0.0005)	(0.0058)	(0.0187)
CY GS1 DD >8C	0.0021	0.0047	-0.0014*	-0.0150*	0.0865**
	(0.0021)	(0.0124)	(0.0008)	(0.0078)	(0.0349)
CY GS2 DD >8C	-0.0008*	-0.0070**	-0.0004*	-0.0034	0.0041
	(0.0005)	(0.0032)	(0.0002)	(0.0022)	(0.0080)
Village FE	Yes	Yes	Yes	Yes	Yes
District-by-Year FE	Yes	Yes	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Observations	3726	3726	6210	6210	3726
R^2	0.371	0.389	0.607	0.667	0.174

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use and 3 survey rounds (2003-04, 2006-07 and 2009-10) for pesticides and weeding labor days. The table presents the effects of temperature (captured via degree days (DD) over 8C) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table D.15: Honoré Fixed Effects Tobit: Temperature, Fertilizer and Pesticide Use

	(1) Ln Pesticide/Acre β / SE	(2) Ln Fertilizer/Acre β / SE	(3) Own Weeding Days/Acre β / SE
CY PP DD >8C	0.0142	-0.0052	0.0466*
	(0.0106)	(0.0057)	(0.0263)
CY GS1 DD >8C	0.0277***	-0.0231***	-0.0239
	(0.0076)	(0.0063)	(0.0255)
CY GS2 DD >8C	-0.0055	0.0031	0.0220
	(0.0032)	(0.0026)	(0.0143)
Village FE	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes
Observations	3726	6210	3726

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use and 3 survey rounds (2003-04, 2006-07 and 2009-10) for pesticides and weeding labor days. The table presents the effects of temperature (captured via degree days (DD) over 8C) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table D.16: Standard Tobit Estimates: Temperature, Fertilizer and Pesticide Use

	(1) Ln Pesticide/Acre β / SE	(2) Ln Fertilizer/Acre β / SE	(3) Own Weeding Days/Acre β / SE
CY PP DD >8C	0.0179	-0.0048	0.0199**
	(0.0120)	(0.0055)	(0.0098)
CY GS1 DD >8C	0.0381***	-0.0216***	-0.0189
	(0.0108)	(0.0066)	(0.0124)
CY GS2 DD >8C	-0.0057	0.0019	0.0092
	(0.0044)	(0.0027)	(0.0062)
Village FE	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes
Observations	3726	6210	3726

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use and 3 survey rounds (2003-04, 2006-07 and 2009-10) for pesticides and weeding labor days. The table presents the effects of temperature (captured via degree days (DD) over 8C) on weeding labor. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table D.17: Uniform Maize Crop Calendar: Temperature, Fertilizer and Pesticide Use

	(1) Pesticides 0/1 β / SE	(2) Ln Pesticide/Acre β / SE	(3) Fertilizer 0/1 β / SE	(4) Ln Fertilizer/Acre β / SE	(5) Own Weeding Days/Acre β / SE
CY PP DD >8C	0.0021**	0.0148**	-0.0003	-0.0051	-0.0008
	(0.0011)	(0.0073)	(0.0005)	(0.0051)	(0.0125)
CY GS1 DD >8C	0.0043**	0.0283**	-0.0013	-0.0106	0.0262
	(0.0017)	(0.0119)	(0.0008)	(0.0078)	(0.0262)
CY GS2 DD >8C	-0.0012*	-0.0078*	-0.0000	0.0002	0.0020
	(0.0006)	(0.0046)	(0.0003)	(0.0025)	(0.0110)
Village FE	Yes	Yes	Yes	Yes	Yes
Province-by-Year FE	Yes	Yes	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Observations	3726	3726	6210	6210	3726
R^2	0.341	0.357	0.594	0.657	0.164

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use and 3 survey rounds (2003-04, 2006-07 and 2009-10) for pesticides and weeding labor days. The table presents the effects of temperature (captured via degree days (DD) over 8C) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table D.18: Uniform Maize Crop Calendar, Drop Eastern Province: Temperature, Fertilizer and Pesticide Use

	(1) Pesticides 0/1 β / SE	(2) Ln Pesticide/Acre β / SE	(3) Fertilizer 0/1 β / SE	(4) Ln Fertilizer/Acre β / SE	(5) Own Weeding Days/Acre β / SE
CY PP DD >8C	0.0021	0.0124	0.0000	0.0004	-0.0037
	(0.0014)	(0.0097)	(0.0005)	(0.0054)	(0.0167)
CY GS1 DD >8C	0.0039**	0.0225*	-0.0015	-0.0135*	0.0306
	(0.0017)	(0.0122)	(0.0009)	(0.0081)	(0.0290)
CY GS2 DD >8C	-0.0011	-0.0074	0.0001	0.0031	-0.0009
	(0.0007)	(0.0050)	(0.0003)	(0.0025)	(0.0121)
Village FE	Yes	Yes	Yes	Yes	Yes
Province-by-Year FE	Yes	Yes	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Observations	3093	3093	5155	5155	3093
R^2	0.307	0.332	0.611	0.662	0.164

Notes: Sample includes 1031 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use and 3 survey rounds (2003-04, 2006-07 and 2009-10) for pesticides and weeding labor days. The table presents the effects of temperature (captured via degree days (DD) over 8C) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table D.19: Conley Standard Errors: Temperature, Fertilizer and Pesticide Use

	(1) Pesticides 0/1	(2) Ln Pesticide/Acre	(3) Fertilizer 0/1	(4) Ln Fertilizer/Acre	(5) Own Weeding Days/Acre
	β / SE	β / SE	β / SE	β / SE	β / SE
CY PP DD >8C	0.0010	0.0067	-0.0004	-0.0044*	0.0171***
	(0.0008)	(0.0053)	(0.0002)	(0.0025)	(0.0032)
CY GS1 DD >8C	0.0027***	0.0214***	-0.0013**	-0.0131**	-0.0068
	(0.0008)	(0.0055)	(0.0006)	(0.0053)	(0.0106)
CY GS2 DD >8C	-0.0005	-0.0022	-0.0000	0.0005	0.0049
	(0.0005)	(0.0033)	(0.0001)	(0.0012)	(0.0045)
Village FE	Yes	Yes	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Observations	3726	3726	6210	6210	3726
R^2	0.044	0.047	0.018	0.023	0.011

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use and 3 survey rounds (2003-04, 2006-07 and 2009-10) for pesticides and weeding labor days. The table presents the effects of temperature on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are adjusted to reflect spatial dependence as modeled in (103). Spatial autocorrelation is assumed to linearly decrease in distance up to a cutoff of 500 km.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table D.20: Standard Errors Clustered at Grid Point Level: Temperature, Fertilizer and Pesticide Use

	(1) Pesticides 0/1	(2) Ln Pesticide/Acre	(3) Fertilizer 0/1	(4) Ln Fertilizer/Acre	(5) Own Weeding Days/Acre
	β / SE	β / SE	β / SE	β / SE	β / SE
CY PP DD >8C	0.0010	0.0067	-0.0004	-0.0044	0.0171**
	(0.0014)	(0.0095)	(0.0005)	(0.0046)	(0.0066)
CY GS1 DD >8C	0.0027**	0.0214**	-0.0013**	-0.0131**	-0.0068
	(0.0011)	(0.0076)	(0.0005)	(0.0056)	(0.0151)
CY GS2 DD >8C	-0.0005	-0.0022	-0.0000	0.0005	0.0049
	(0.0005)	(0.0036)	(0.0002)	(0.0019)	(0.0050)
Village FE	Yes	Yes	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Observations	3726	3726	6210	6210	3726
R^2	0.336	0.353	0.594	0.657	0.164

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use and 3 survey rounds (2003-04, 2006-07 and 2009-10) for pesticides and weeding labor days. The table presents the effects of temperature (captured via degree days (DD) over 8C) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses. Standard errors are in parentheses, clustered by grid point.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table D.21: Cluster-Bootstrap P-Values at Grid Point Level: Temperature, Fertilizer and Pesticide Use

	(1) Pesticides 0/1 β / SE	(2) Ln Pesticide/Acre β / SE	(3) Fertilizer 0/1 β / SE	(4) Ln Fertilizer/Acre β / SE	(5) Own Weeding Days/Acre β / SE
CY PP DD >8C	0.0010	0.0067	-0.0004	-0.0044	0.0171
	(0.49)	(0.66)	(0.45)	(0.44)	(0.03)
CY GS1 DD >8C	0.0027	0.0214	-0.0013	-0.0131	-0.0068
	(0.09)	(0.05)	(0.01)	(0.01)	(0.69)
CY GS2 DD >8C	-0.0005	-0.0022	-0.0000	0.0005	0.0049
	(0.04)	(0.55)	(0.95)	(0.85)	(0.37)
Village FE	Yes	Yes	Yes	Yes	Yes
Prov-Specific Time Trends	Yes	Yes	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Observations	3726	3726	6210	6210	3726
R^2	0.336	0.353	0.594	0.657	0.164

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use and 3 survey rounds (2003-04, 2006-07 and 2009-10) for pesticides and weeding labor days. The table presents the effects of temperature (captured via degree days (DD) over 8C) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are clustered by grid point (200 replications). **P-values are in parentheses.**

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table D.22: Log Total Maize Output and Temperature

	(1) Log Maize Yield/Acre (Kg.) β / SE
CY PP DD >8C	0.0018
	(0.0033)
CY GS1 DD >8C	-0.0038*
	(0.0023)
CY GS2 DD >8C	0.0006
	(0.0015)
Village FE	Yes
Province-by-Year FE	Yes
Rainfall Controls	Yes
Observations	6210
R^2	0.374

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10). The table presents the effects of temperature (captured via degree days (DD) over 8C) on total maize output. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table D.23: Accounting for Within-Day Temperature Variation: Log Total Maize Output and Temperature

	(1) Log Yield/Acre β / SE	(2) Log Yield/Acre β / SE	(3) Log Yield/Acre β / SE	(4) Log Yield/Acre β / SE	(5) Log Yield/Acre β / SE
CY PP DD >21C II	0.0021				
	(0.0043)				
CY GS1 DD >21C II	-0.0083**				
	(0.0033)				
CY GS2 DD >21C II	0.0002				
	(0.0029)				
CY PP DD >22C II		0.0034			
		(0.0044)			
CY GS1 DD >22C II		-0.0089***			
		(0.0030)			
CY GS2 DD >22C II		0.0010			
		(0.0037)			
CY PP DD >23C II			0.0043		
			(0.0058)		
CY GS1 DD >23C II			-0.0063		
			(0.0048)		
CY GS2 DD >23C II			0.0027		
			(0.0050)		
CY PP DD >24C II				0.0058	
				(0.0064)	
CY GS1 DD >24C II				-0.0094	
				(0.0076)	
CY GS2 DD >24C II				0.0066	
				(0.0068)	
CY PP DD >25C II					0.0077
					(0.0076)
CY GS1 DD >25C II					-0.0095
					(0.0109)
CY GS2 DD >25C II					0.0132
					(0.0092)
Village FE	Yes	Yes	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Observations	6210	6210	6210	6210	6210
R^2	0.375	0.375	0.374	0.375	0.376

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10). The table presents the effects of temperature (captured via degree days (DD)) on total maize output. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table D.24: Temperature, Pesticides and Fertilizer Use, by Wealth (Round 1)

	(1) Pesticides 0/1	(2) Ln Pesticide/Acre	(3) Fertilizer 0/1	(4) Ln Fertilizer/Acre	(5) Own Weeding Days/Acre
	β / SE	β / SE	β / SE	β / SE	β / SE
CY PP DD >8C	0.0015	0.0104	-0.0003	-0.0043	0.0188
	(0.0010)	(0.0071)	(0.0004)	(0.0046)	(0.0115)
CY GS1 DD >8C	0.0031***	0.0238***	-0.0009	-0.0111*	0.0121
	(0.0012)	(0.0076)	(0.0006)	(0.0060)	(0.0163)
CY GS2 DD >8C	-0.0003	-0.0013	-0.0000	0.0003	0.0061
	(0.0005)	(0.0036)	(0.0002)	(0.0022)	(0.0077)
CY PP DD >8C*Bottom Wealth Tercile	-0.0009**	-0.0075***	-0.0002	-0.0010	-0.0057
	(0.0005)	(0.0028)	(0.0003)	(0.0026)	(0.0097)
CY GS1 DD >8C*Bottom Wealth Tercile	-0.0005	-0.0021	-0.0008**	-0.0041	-0.0405*
	(0.0009)	(0.0054)	(0.0004)	(0.0037)	(0.0214)
CY GS2 DD >8C*Bottom Wealth Tercile	-0.0004	-0.0025	0.0002	0.0013	-0.0051
	(0.0005)	(0.0031)	(0.0003)	(0.0024)	(0.0116)
Household FE	Yes	Yes	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Observations	3726	3726	6210	6210	3726
R^2	0.587	0.588	0.740	0.789	0.479

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use and 3 survey rounds (2003-04, 2006-07 and 2009-10) for pesticides. The table presents the heterogeneous effects of temperature (captured via degree days (DD) over 8C) on agricultural input use, by wealth. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table D.25: Standard Tobit Estimates: Temperature, Pesticides and Fertilizer Use, by Wealth (Round 1)

	(1) Ln Pesticide/Acre β / SE	(2) Ln Fertilizer/Acre β / SE	(3) Own Weeding Days/Acre β / SE
CY PP DD >8C	0.0208*	-0.0047	0.0188
	(0.0125)	(0.0057)	(0.0116)
CY GS1 DD >8C	0.0410***	-0.0192**	0.0078
	(0.0119)	(0.0076)	(0.0154)
CY GS2 DD >8C	-0.0057	0.0022	0.0095
	(0.0043)	(0.0029)	(0.0070)
CY PP DD >8C*Bottom Wealth Tercile	-0.0071	-0.0022	-0.0036
	(0.0058)	(0.0034)	(0.0091)
CY GS1 DD >8C*Bottom Wealth Tercile	-0.0043	-0.0063	-0.0557***
	(0.0111)	(0.0058)	(0.0193)
CY GS2 DD >8C*Bottom Wealth Tercile	-0.0028	0.0018	0.0009
	(0.0045)	(0.0030)	(0.0101)
Household FE	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes
Observations	3726	6210	3726
R^2			

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use and 3 survey rounds (2003-04, 2006-07 and 2009-10) for pesticides. The table presents the heterogeneous effects of temperature (captured via degree days (DD) over 8C) on agricultural input use, by wealth. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table D.26: Honoré Fixed Effects Tobit: Temperature, Pesticides and Fertilizer Use, by Wealth (Round 1)

	(1) Ln Pesticide/Acre β / SE	(2) Ln Fertilizer/Acre β / SE	(3) Own Weeding Days/Acre β / SE
CY PP DD >8C	0.0162**	-0.0048	0.0373
	(0.0064)	(0.0039)	(0.0366)
CY GS1 DD >8C	0.0292***	-0.0201***	0.0257
	(0.0072)	(0.0054)	(0.0345)
CY GS2 DD >8C	-0.0051	0.0028	0.0192
	(0.0026)	(0.0021)	(0.0204)
CY PP DD >8C*Bottom Wealth Tercile	-0.0062	-0.0021	0.0013
	(0.0047)	(0.0027)	(0.0205)
CY GS1 DD >8C*Bottom Wealth Tercile	-0.0027	-0.0057	-0.0979***
	(0.0081)	(0.0051)	(0.0334)
CY GS2 DD >8C*Bottom Wealth Tercile	-0.0014	0.0016	0.0102
	(0.0041)	(0.0026)	(0.0217)
Household FE	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes
Observations	3726	6210	3726

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use and 3 survey rounds (2003-04, 2006-07 and 2009-10) for pesticides. The table presents the heterogeneous effects of temperature (captured via degree days (DD) over 8C) on agricultural input use, by wealth. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table D.27: Temperature, Pesticides and Fertilizer Use, by Wealth (Round 1-5)

	(1)	(2)	(3)	(4)	(5)
	Pesticides 0/1	Ln Pesticide/Acre	Fertilizer 0/1	Ln Fertilizer/Acre	Own Weeding Days/Acre
	β / SE	β / SE	β / SE	β / SE	β / SE
CY PP DD >8C	0.0015	0.0099	-0.0003	-0.0043	0.0159
	(0.0010)	(0.0071)	(0.0004)	(0.0046)	(0.0114)
CY GS1 DD >8C	0.0030***	0.0230***	-0.0009	-0.0110*	0.0055
	(0.0011)	(0.0074)	(0.0006)	(0.0059)	(0.0151)
CY GS2 DD >8C	-0.0004	-0.0016	-0.0001	-0.0000	0.0049
	(0.0005)	(0.0036)	(0.0002)	(0.0021)	(0.0073)
CY PP DD >8C*Bottom Wealth Tercile	-0.0010**	-0.0069**	-0.0002	-0.0012	0.0006
	(0.0005)	(0.0028)	(0.0003)	(0.0027)	(0.0082)
CY GS1 DD >8C*Bottom Wealth Tercile	-0.0002	-0.0008	-0.0007*	-0.0040	-0.0286*
	(0.0008)	(0.0049)	(0.0004)	(0.0035)	(0.0165)
CY GS2 DD >8C*Bottom Wealth Tercile	-0.0001	-0.0014	0.0004	0.0028	-0.0004
	(0.0005)	(0.0031)	(0.0002)	(0.0025)	(0.0112)
Household FE	Yes	Yes	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Observations	3726	3726	6210	6210	3726
R^2	0.587	0.587	0.740	0.789	0.478

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use and 3 survey rounds (2003-04, 2006-07 and 2009-10) for pesticides. The table presents the heterogeneous effects of temperature (captured via degree days (DD) over 8C) on agricultural input use, by wealth. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table D.28: Standard Tobit Estimates: Temperature, Pesticides and Fertilizer Use, by Wealth (Round 1-5)

	(1) Ln Pesticide/Acre β / SE	(2) Ln Fertilizer/Acre β / SE	(3) Own Weeding Days/Acre β / SE
CY PP DD >8C	0.0207*	-0.0045	0.0158
	(0.0125)	(0.0057)	(0.0113)
CY GS1 DD >8C	0.0397***	-0.0192***	0.0001
	(0.0115)	(0.0073)	(0.0143)
CY GS2 DD >8C	-0.0063	0.0017	0.0088
	(0.0041)	(0.0028)	(0.0066)
CY PP DD >8C*Bottom Wealth Tercile	-0.0079	-0.0030	0.0037
	(0.0053)	(0.0037)	(0.0079)
CY GS1 DD >8C*Bottom Wealth Tercile	-0.0008	-0.0058	-0.0421***
	(0.0097)	(0.0055)	(0.0153)
CY GS2 DD >8C*Bottom Wealth Tercile	0.0001	0.0037	0.0029
	(0.0046)	(0.0030)	(0.0097)
Household FE	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes
Observations	3726	6210	3726

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use and 3 survey rounds (2003-04, 2006-07 and 2009-10) for pesticides. The table presents the heterogeneous effects of temperature (captured via degree days (DD) over 8C) on agricultural input use, by wealth. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table D.29: Honoré Fixed Effects Tobit: Temperature, Pesticides and Fertilizer Use, by Wealth (Round 1-5)

	(1) Ln Pesticide/Acre β / SE	(2) Ln Fertilizer/Acre β / SE	(3) Own Weeding Days/Acre β / SE
CY PP DD >8C	0.0158**	-0.0049	0.0330
	(0.0064)	(0.0039)	(0.0362)
CY GS1 DD >8C	0.0293***	-0.0201***	0.0110
	(0.0074)	(0.0055)	(0.0357)
CY GS2 DD >8C	-0.0055*	0.0024	0.0175
	(0.0025)	(0.0020)	(0.0197)
CY PP DD >8C*Bottom Wealth Tercile	-0.0060	-0.0021	0.0117
	(0.0049)	(0.0028)	(0.0197)
CY GS1 DD >8C*Bottom Wealth Tercile	-0.0024	-0.0053	-0.0721**
	(0.0081)	(0.0051)	(0.0344)
CY GS2 DD >8C*Bottom Wealth Tercile	0.0005	0.0033	0.0147
	(0.0043)	(0.0027)	(0.0237)
Household FE	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes
Observations	3726	6210	3726

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use and 3 survey rounds (2003-04, 2006-07 and 2009-10) for pesticides. The table presents the heterogeneous effects of temperature (captured via degree days (DD) over 8C) on agricultural input use, by wealth. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table D.30: Controls for Daily Humidity: Temperature, Pesticides and Weeding Labor Days

	(1) Pesticides 0/1 β / SE	(2) Ln Pesticide/Acre β / SE	(3) Own Weeding Days/Acre β / SE
CY PP DD >8C	0.0015*	0.0079	0.0053
	(0.0008)	(0.0054)	(0.0111)
CY GS1 DD >8C	0.0027***	0.0220***	-0.0032
	(0.0009)	(0.0062)	(0.0126)
CY GS2 DD >8C	-0.0005	-0.0030	0.0029
	(0.0004)	(0.0029)	(0.0061)
Village FE	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes
Humidity Controls	Yes	Yes	Yes
Observations	3726	3726	3726
R^2	0.338	0.355	0.165

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use and 3 survey rounds (2003-04, 2006-07 and 2009-10) for pesticides and weeding labor days. The table presents the effects of temperature (captured via degree days (DD) over 8C) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table D.31: Controls for Soil Moisture: Temperature and Fertilizer Use

	(1) Fertilizer 0/1 β / SE	(2) Fertilizer 0/1 β / SE	(3) Ln Fertilizer/Acre β / SE	(4) Ln Fertilizer/Acre β / SE
CY PP DD >8C	-0.0004	-0.0001	-0.0044	-0.0034
	(0.0004)	(0.0006)	(0.0042)	(0.0063)
CY GS1 DD >8C	-0.0013**	-0.0016*	-0.0131**	-0.0133
	(0.0005)	(0.0009)	(0.0050)	(0.0082)
CY GS2 DD >8C	-0.0000	-0.0004	0.0005	-0.0032
	(0.0002)	(0.0002)	(0.0019)	(0.0022)
Village FE	Yes	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes	Yes
Soil Moisture Controls	No	Yes	No	Yes
Observations	6210	2352	6210	2352
R^2	0.594	0.589	0.657	0.646

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use. The table presents the effects of temperature (captured via degree days (DD) over 8C) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table D.32: Rainfall Coefficients: Temperature, Fertilizer and Pesticide Use

	(1) Pesticides 0/1 β / SE	(2) Ln Pesticide/Acre β / SE	(3) Fertilizer 0/1 β / SE	(4) Ln Fertilizer/Acre β / SE	(5) Own Weeding Days/Acre β / SE
CY PP DD >8C	0.0010	0.0067	-0.0004	-0.0044	0.0171**
	(0.0008)	(0.0058)	(0.0004)	(0.0042)	(0.0086)
CY GS1 DD >8C	0.0027***	0.0214***	-0.0013**	-0.0131**	-0.0068
	(0.0009)	(0.0058)	(0.0005)	(0.0050)	(0.0117)
CY GS2 DD >8C	-0.0005	-0.0022	-0.0000	0.0005	0.0049
	(0.0004)	(0.0029)	(0.0002)	(0.0019)	(0.0062)
CY PP Rain Bottom Tercile	0.0173	0.1992	-0.0055	0.0235	0.5520
	(0.0327)	(0.2045)	(0.0144)	(0.1448)	(0.4497)
CY PP Rain Top Tercile	0.0001	0.0804	-0.0056	0.0721	0.4659
	(0.0391)	(0.2197)	(0.0215)	(0.2092)	(0.5053)
CY GS1 Rain Bottom Tercile	0.0716*	0.3051	0.0024	0.0085	0.9740**
	(0.0370)	(0.2436)	(0.0165)	(0.1770)	(0.3962)
CY GS1 Rain Top Tercile	0.0402	-0.0787	-0.0342**	-0.3063*	-0.2206
	(0.0391)	(0.2660)	(0.0147)	(0.1556)	(0.5700)
CY GS2 Rain Bottom Tercile	-0.0485	-0.2918	-0.0489**	-0.5361***	-0.5438
	(0.0373)	(0.2565)	(0.0204)	(0.1877)	(0.7960)
CY GS2 Rain Top Tercile	-0.0911**	-0.7127**	-0.0076	-0.0916	-1.0003
	(0.0428)	(0.2920)	(0.0148)	(0.1483)	(0.7652)
Village FE	Yes	Yes	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	3726	3726	6210	6210	3726
R^2	0.336	0.353	0.594	0.657	0.164

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use and 3 survey rounds (2003-04, 2006-07 and 2009-10) for pesticides and weeding labor days. The table presents the effects of temperature (captured via degree days (DD) over 8C) on agricultural input use. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table D.33: Rainfall Coefficients: Log Total Maize Output and Temperature

	(1) Log Maize Yield/Acre (Kg.) β / SE
CY PP DD >8C	0.0018
	(0.0033)
CY GS1 DD >8C	-0.0038*
	(0.0023)
CY GS2 DD >8C	0.0006
	(0.0015)
CY PP Rain Bottom Tercile	-0.2430**
	(0.1020)
CY PP Rain Top Tercile	0.1067
	(0.0831)
CY GS1 Rain Bottom Tercile	0.0804
	(0.0823)
CY GS1 Rain Top Tercile	-0.1130
	(0.1071)
CY GS2 Rain Bottom Tercile	-0.0904
	(0.1173)
CY GS2 Rain Top Tercile	0.3880***
	(0.1129)
Village FE	Yes
Prov-by-Year FE	Yes
Observations	6210
R^2	0.374

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10). The table presents the effects of temperature (captured via degree days (DD) over 8C) on total maize output. CY: current year; PP: pre-planting or land preparation - onset of planting; GS1: planting or basal fertilizer application - onset of top dressing fertilizer; GS2: top dressing fertilizer application - onset harvest. Standard errors are in parentheses, clustered by village.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table D.34: Log Total Maize Output and Agricultural Inputs

	(1) Log Yield/Acre β / SE	(2) Log Yield/Acre β / SE
Ln Pesticide/Acre	0.0268**	
	(0.0118)	
Ln Fertilizer/Acre		0.0355***
		(0.0112)
Household FE	Yes	Yes
Village-by-Year FE	Yes	Yes
Observations	3726	6210
R^2	0.695	0.650

Notes: Sample includes 1242 households balanced over 5 survey rounds (1996-97, 1999-00, 2003-04, 2006-07 and 2009-10) for fertilizer use and 3 survey rounds (2003-04, 2006-07 and 2009-10) for pesticide use. The table presents the effects of pesticide and fertilizer use on total maize output. Standard errors are in parentheses, clustered by village.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

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